INTELLIGENT RF-BASED INDOOR LOCALIZATION THROUGH RSSI USING LORA COMMUNICATION TECHNOLOGY

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Field of Study	Engineering Technology
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The Graduate School of Thai-Nichi Institute of Technology has been approved and accepted as partial fulfillment of the requirement for the Master's Degree

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This thesis has proposed indoor localization approaches. where the increase in ubiquitous computing and context-dependent have led to an emphasis on a continuous search for promising localization technologies and techniques. Typical RF-Based localization technologies such as Cellular, RFID, Bluetooth, Wi-Fi, Zigbee, and UWB have been widespread studied over the past decades. Recently, LoRa communication technology has been suggested as a potential alternative to those of exiting wireless communication standards with low power consumption and low implementation costs. This thesis therefore presents an indoor localization technique through the use of Received Signal Strength Indicator (RSSI) of LoRa Technology. The LoRa chip from SEMTECH utilized on a compact board with built-in antenna. The Arduino microcontroller employed as a core processor with a step-down switching regulator. Five sets of LoRa nodes were implemented and four of which were utilized as static nodes, radiating a signal power from 5-meter high from the floor. The receiving node placed in a particular coordinate on the floor. The Received Signal Strength values were employed as inputs for Artificial Neural Network (ANN) for estimation of the coordination of the receiving node. The accuracy was approximately 95%. The results provide satisfactory accuracy and low-power operation as for an alternative for large scales deployments of indoor localization.

Graduate School	Student's Signature………………………
Field of Study Engineering Technology	Advisor's Signature………………………
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Sittikorn Muekdang

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Introduction

1.1 Introduction

1.1.1 Low-Power Wide-Area Networks

The purpose of this thesis is to give an introductory technical overview to LoRa® and LoRaWAN™. Low–Power, Wide-Area Networks (LPWAN) are projected to support a major portion of the billions of devices forecasted for the Internet of Things (IoT). LoRaWAN™ is designed from the bottom up to optimize LPWANs for battery lifetime, capacity, range, and cost. A summary of the LoRaWAN™ specification for the different regions will be given as well as high level comparison of the different technologies competing in the LPWAN space.

LoRa® is the physical layer or the wireless modulation utilized to create the long-range communication link. Many legacy wireless systems use Frequency Shifting Keying (FSK) modulation as the physical layer because it is a very efficient modulation for achieving low power. LoRa® is based on chirp spread spectrum modulation, which maintains the same low power characteristics as FSK modulation but significantly increases the communication range. Chirp spread spectrum has been used in military and space communication for decades due to the long communication distances that can be achieved and robustness to interference, but LoRa® is the first low cost implementation for commercial usage, as shown in Figure 1.2.

The advantage of LoRa® is its. long-range capability. A single gateway or base station can cover entire cities or hundreds of square kilometers. Range highly depends on the environment or obstructions in a given location, but LoRa® and LoRaWAN™ have a link budget greater than any other standardized communication technology. The link budget, typically given in decibels (dB), is the primary factor in determining the range in a given environment. Figure 1 are the coverage maps from the Proximus network deployed in Belgium. With a minimal amount of infrastructure, entire countries can easily be covered.

Figure 1.1 A single gateway can cover countries entire cities of square kilometers

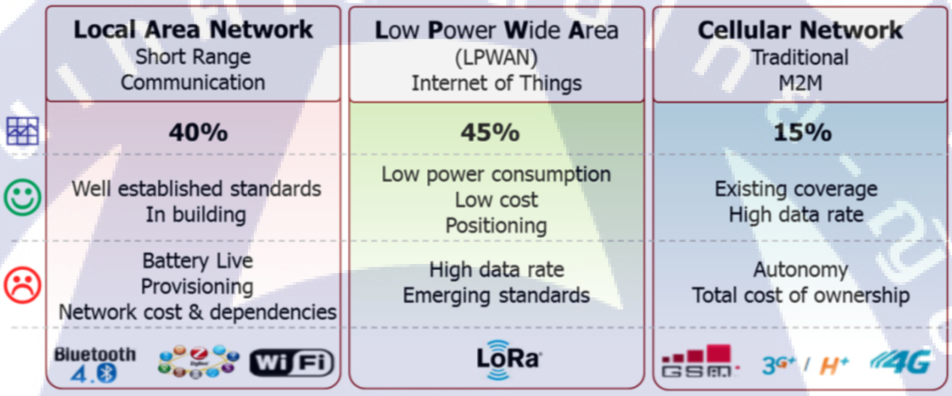


Figure 1.2 IoT Technology Comparison

One technology cannot serve all of the projected applications and volumes for IoT. WiFi and BLE are widely adopted standards and serve the applications related to communicating personal devices quite well. Cellular technology is a great fit for applications that need high data throughput and have a power source. LPWAN offers multi-year battery lifetime and is designed for sensors and applications that need to send small amounts of data over long distances a few times per hour from varying environments.

The essential difference between the Internet and “the Internet of Things” (IoT) [1] is that in the IoT, there is just less of everything available in a given device or network device: less memory, less processing power, less bandwidth and of course, less available energy. This is either because “things” are battery driven and maximizing lifetime is a priority or because their number is expected to be massive it is estimated that there will be 50 billion connected devices by 2020 [2]. This drive to do more with less leads to constraints that limit the applicability of traditional cellular networks, as well as of technologies, such as WIFI, due to energy and scalability requirements. Another range of protocols and technologies has emerged to fulfill the communication requirements of the IoT: Low-Power Wide Area Networks (LPWAN). Colloquially speaking, an LPWAN is supposed to be to the IoT WiFi was to consumer networking: offering radio coverage over a very large area by way of base stations and adapting transmission rates, transmission power, modulation, duty cycles, such that end-devices incur a very low energy consumption due to them being connected. LoRa® is one such LPWAN protocol and the subject of study for this thesis. LoRa targets deployments where end-devices have limited energy where end-devices do not need to transmit more than a few bytes at a time [3] and where data traffic can be initiated either by the end-device (such as when the end-device is a sensor) or by an external entity wishing to communicate with the end-device (such as when the end-device is an actuator). The long-range and low-power nature of LoRa makes it an interesting candidate for smart sensing technology in civil infrastructures (such as health monitoring, smart metering, environment monitoring, etc.), as well as in industrial applications.

1.1.2 Indoor positioning

Indoor Positioning Systems (IPS) use sensors and communication technologies to locate objects in indoor environments. IPS are attracting scientific and enterprise interest because there is a big market opportunity for applying these technologies. There are many previous surveys on indoor positioning systems however, most of them lack a solid classification scheme that would structurally map a wide field such as IPS, or omit several key technologies or have a limited perspective; finally, surveys rapidly become obsolete in an area as dynamic as IPS. The goal of this thesis is to provide a technological perspective of indoor positioning systems, comprising a LoRa® technology classify the existing approaches in a structure in order to guide the review and discussion of the different approaches.

Finally, present a comparison of indoor positioning approaches and present the evolution and trends that foresee, as shown in Figure 1.3.

1.1.3 Location based services and indoor navigation in railway stations

1.1.3.1 Railway station solutions

Modern railway stations must satisfy high requirements: of course, it is extremely important that passengers reach their destination fast and safe. Especially people with reduced mobility may welcome support. The large number of merchants wishes for a good platform to present themselves and the possibility to realize location-based advertising. For the station operator a lot of opportunities arise considering facility management.

1.1.3.2 Advantages for merchants and restaurants

Merchants can send their potential customers tailored offers – for example picking those who have already been to similar shops or who are returning visitors. And for sure everyone is delighted by a discount of his favorite shop pushed directly on his smartphone.

Figure 1.3 Location based services and indoor navigation in railway stations

1.1.3.3 Advantages for railway station operators

Using indoor location analytics, station operators gain a lot of information about visitor flows inside the building. With a clearly arranged web interface they see much frequented areas and can act if it tends to become overcrowded. Based on these data a lot of further functions can be realized, as shown in Figure 1.4.

1.1.4 Location based services and indoor navigation in airport

1.1.4.1 Airport solutions

When people want to go on holiday by plane most of them are both full of anticipation and tension. Business travelers want to keep the waiting times to a minimum and make good use of it. As an airport operator it is goal to offer passengers a trouble-free and comfortable stay. Shops and restaurants wish for passengers who have enough free time to consume, as shown in Figure 1.1.4.3

1.1.4.2 Advantages for passengers

People who travel infrequently may need support in complex infrastructures like airports. Starting holidays relaxed is not so easy when you are confronted with unknown surroundings, tricky routing and foreign languages on journey. Especially people with reduced mobility may have specific requirements.

This is where the benefits of indoor navigation become apparent. It shows the exact routing from car park or railway station to the terminal. It is even possible to implement intermodal door to door navigation. When passengers cover the distance quickly, there still remains enough time to discover shops or take a break in a restaurant. Merchants can push tailored advertising directly to the smartphone and offer a lot of added value for the customer. For example, it could be a coupon or a custom-fit offer. Back from the journey, the airport app helps passengers to find back to their car or public transportation. Business travelers have all information concerning their flight and their boarding pass in their pocket and can quickly find a place to work and relax.

Figure 1.4 Location based services and indoor navigation in airport

1.1.4.3 Advantages for stores and restaurants

Merchants can push custom-fit offers directly to the smartphone of interested clients: For example, those who have already visited this or similar shops. And for sure everyone is delighted by a discount of his favorite shop. In addition, you learn a lot about visitor flows in or nearby the store. Large shops can also use the technique for asset tracking, for example in order to improve theft protection or logistics.

1.1.5 Indoor navigation and location-based services for trade fairs

1.1.5.1 Trade fair solutions

Have you ever wandered through an exhibition, studying a heavy catalogue, looking for interesting exhibitors or for a cash machine, the wardrobe, Perhaps you as an exhibitor had too little or not so interested visitors at exhibition stand. Or perhaps you are a trade fair organizer who wants to assist exhibitors and visitors to take full advantage of their trade fair participation. Modern indoor navigation solutions can solve these problems. A cross-channel trade fair solution provides added value to trade show organizers, exhibitors and visitors, as shown in Figure 1.5.

1.1.5.2 Advantages for trade show organizers

The aim of a trade show organizer is to create an attractive event both for visitors and exhibitors. A trade fair application makes information about exhibitors, services, public transport and framework programmed available to visitors. Personalized content matches the right visitors and exhibitors. With Location Analytics you can analyze visitor flows. During and after the event you can get precise information about hot spots and the number of people in a certain hall or at a stand. The tool also gives you advice on how to optimize routes, for example when they are overcrowded. Exhibitors can sponsor the app and thereby co-finance it

1.1.5.3 Advantages for exhibitors

Of course, exhibitors have the possibility to present themselves on the map of the area in the trade fair app, including pictures, contact data and description. Furthermore, they can use location-based marketing in order to get the attention of the matching visitors. The analysis of visitor flows makes it possible to choose the best stand position.

Figure 1.5 Indoor navigation and location-based services for trade fairs

1.1.6 Indoor navigation and location-based services for office and industry

1.1.6.1 Indoor positioning in office buildings and industry areas

Indoor positioning and indoor navigation can make the management of large offices and industry buildings a lot easier and employees can also benefit from it. For example, can track assets or people, support the security service and offer staff an employee app, as shown in Figure 1.6.

1.1.6.2 Benefits from asset- and staff tracking

Assumed that company site includes a large warehouse, can determine the location of pallets or vehicles by the means of indoor positioning with an accuracy of less than a meter. The position can be displayed for example in an app or web-based platform. It also works with very high storage depots with several levels. It is possible to automatically send a message to the security service when goods leave a defined area. These functions can also be applied to staff and external companies. Both can be integrated in an operation control system, in order to delegate tasks.

1.1.6.3 Advantages for employees

An employee app facilitates work and social contacts for the staff working in large buildings. For example, the application can show them the way to offices and meeting rooms. Can even directly book them. By means of the buddy finder colleagues can exchange their positions and meet up for lunch or an appointment. Further useful and time-saving information which can be included are opening hours and dishes offered by the canteen, departure times of public transport and the position of the employee’s car.

Figure 1.6 Indoor positioning in office buildings and industry areas

1.2 Thesis Outline

1.2.1 Motivation

Coordinate positioning is significant to life facilitation in the modern era. Nowadays, outdoor positioning is possible by the use of acceptable devices such as GPS (Global Positioning System), which leads to multiple benefits, e.g., navigation, positioning for easy reference, and local based services. They are useful and bring more convenience to life. On the contrary, indoor positioning is currently not efficient enough for its accuracy and simplicity due to interference as well as diffraction caused by indoor environments. A positioning device like GPS cannot be manipulated indoor, because signals between GPS receivers and satellites are blocked by building walls. Several indoor positioning approaches, therefore, are designed to eliminate such problem.

The researcher works at Tritech Engineering Co., Ltd., a construction project and AGV auto parts company for industrial plants. So, the researcher realizes a key problem of AGV cars. To clarify, every time when AGV cars are ordered for purchase, a magnetic stripe reader must be installed in the cars as a driving navigator. The cars move on right directions up to the magnetic stripe reader that detects directions/routes from the magnetic stripe installed on the plant floor. The problem found is that after the magnetic stripe is used for a period of time, it will wear out. As a consequence, there are frequent purchase orders for the new ones. And before a new one is installed, the old one must be removed. Therefore, this is not only about too frequent replacement of the magnetic stripe but also the waste of time and installation payment every time when such problem occurs. It leads to the discontinuity of manufacturing processes in industrial plants as it has to wait until the installation or the replacement is finished. This problem inspired the researcher to invent and develop an indoor wireless positioning system as solution of the traditional navigation system of AGV cars.

This thesis presents received signal strength indication (RSSI) for signal transmission by Lora Technology of wireless devices. A Lora receiver is introduced for signal strength measurement. Data processing is conducted for indoor positioning. To implement the test, the LoRa transmitters are installed in the 4 corners of a rectangular building. After that the LoRa receiver is relocated and placed over the different tested coordinates as set in order to obtain RSSI from the 4 LoRa transmitters. Then, RSSI data is processed by a designed ANN model (Artificial Neural Networks) with back-propagation learning algorithm. Supervised learning is imitated for the model design. The model will be applied to the processing afterwards for indoor object or wireless device positioning.

1.2.2 Purposes

The current wireless indoor positioning system have discrepancies more than 1 meter.

1.2.3 Objective

Design an indoor object positioning system by LoRa Technology.

1.2.4 Research Scopes

1.2.4.1 Design an indoor object positioning system by LoRa Technology.

1.2.4.2 Use ANN technique (Artificial Neural Networks) for object positioning inside a large product storage building.

1.2.4.3 LoRa transmitters for the test.

1.2.4.4 LoRa receiver for the test.

1.2.5 Expected Outcomes

Indoor positioning system by LoRa Technology.

1.2.6 Research Plan

The research schedules in Jun 2017 until July 2018.

Table 1.1 Research Plan

Research Methodology	**Year**													
	2017							**2018**						
	6	**7**	**8**	**9**	**10**	**11**	**12**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1. A preliminary study on the Indoor localization system.														
2. Study of the structure of indoor localization and communication system.														
3. Design and Create of indoor localization system.														
4. Experimental and improvement of the indoor localization system.														
5. Analysis and summary of the experimental result including the conclusion.														
6. Summary of research and presentation.														

1.2.7 Keyword Descriptions

1.2.7.1 Indoor Localization

An indoor positioning system (IPS) is a system to locate objects or people inside a building using lights, radio waves, magnetic fields, acoustic signals, or other sensory information collected by mobile devices. There are several commercial systems on the market, but there is no standard for an IPS system.

1.2.7.2 LoRa Technology

LoRa is a 'Long Range' low power wireless standard intended for providing a cellular style low data rate communications network. LoRa is ideal for providing intermittent low data rate connectivity over significant distances. The radio interface has been designed to enable extremely low signal levels to be received, and as a result even low power transmissions can be received at significant ranges. The LoRa modulation and radio interface has been designed and optimized to provide exactly the type of communications needed for remote IoT and M2M nodes.

1.2.7.3 Received Signal Strength Indication

RSSI, or “Received Signal Strength Indicator”, is a measurement of how well device can hear a signal from an access point or router. It’s a value that is useful for determining if you have enough signal to get a good wireless connection.

1.2.7.4 Artificial Neural Network

An artificial neuron network (ANN) is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes - or learns, in a sense - based on that input and output. ANNs are considered nonlinear statistical data modeling tools where the complex relationships between inputs and outputs are modeled or patterns are found. ANN is also known as a neural network.

Chapter 2
Related Theories and Literature Reviews

2.1 Related Theories

2.1.1 LoRaWAN Technology

LoRaWAN™ defines the communication protocol and system architecture for the network while the LoRa® physical layer enables the long-range communication link. The protocol and network architecture have the most influence in determining the battery lifetime of a node, the network capacity, the quality of service, the security, and the variety of applications served by the network as can be seen in Figure 2.1.

2.1.1.1 Network Architecture

Many existing deployed networks utilize a mesh network architecture. In a mesh network, the individual end-nodes forward the information of other nodes to increase the communication range and cell size of the network. While this increases the range, it also adds complexity, reduces network capacity, and reduces battery lifetime as nodes receive and forward information from other nodes that is likely irrelevant for them. Long range star architecture makes the most sense for preserving battery lifetime when long-range connectivity can be achieved as can be seen in Figure 2.2.

In a LoRaWAN™ network nodes are not associated with a specific gateway. Instead, data transmitted by a node is typically received by multiple gateways. Each gateway will forward the received packet from the end-node to the cloud-based network server via some backhaul (either cellular, Ethernet, satellite, or Wi-Fi). The intelligence and complexity are pushed to the network server, which manages the network and will filter redundant received packets, perform security checks, schedule acknowledgments through the optimal gateway, and perform adaptive data rate, etc. If a node is mobile or moving there is no handover needed from gateway to gateway, which is a critical feature to enable asset tracking applications–a major target application vertical for IoT.

<table>
<tr><th colspan="5">Application</th></tr>
<tr><th colspan="5">LoRa® MAC</th></tr>
<tr><td colspan="5">MAC options</td></tr>
<tr><td colspan="2">Class A
(Baseline)</td><td>Class B
(Baseline)</td><td colspan="2">Class C
(Continuous)</td></tr>
<tr><th colspan="5">LoRa® Modulation</th></tr>
<tr><td colspan="5">Regional ISM band</td></tr>
<tr><td>EU 868</td><td>EU 433</td><td>US 915</td><td>AS 430</td><td>-</td></tr>
</table>

Figure 2.1 Built on the LoRa® PHY, the LoRaWAN media access control (MAC) defines the message formats for different device classes

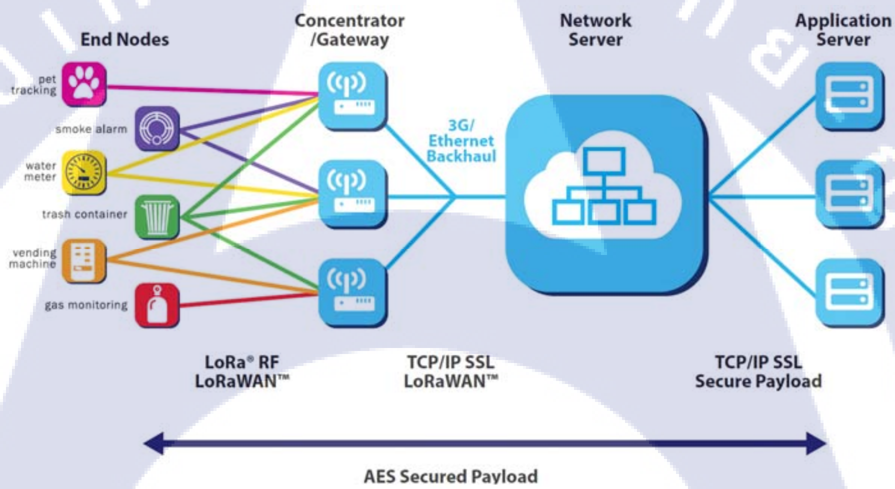


Figure 2.2 The LoRa network architecture

A typical LoRa® network is “a star-of-stars topology”, which includes three different types of devices, as shown in Figure 2.3.

The basic architecture of a LoRaWAN network is as follows: end-devices communicate with gateways using LoRa® with LoRaWAN. Gateways forward raw LoRaWAN frames from devices to a network server over a backhaul interface with a higher throughput, typically Ethernet or 3G. Consequently, gateways are only bidirectional relays, or protocol converters, with the network server being responsible for decoding the packets sent by the devices and generating the packets that should be sent back to the devices. There are three classes of LoRa® end-devices, which differ only with regards to the downlink scheduling. A Study of LoRa®: Long Range & Low Power Networks for the Internet of Things.

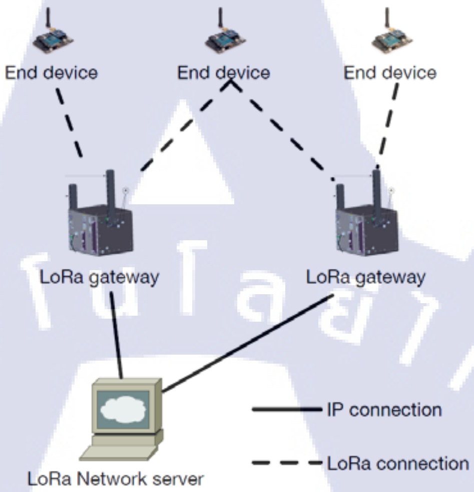


Figure 2.3 The basic architecture of a LoRaWAN network

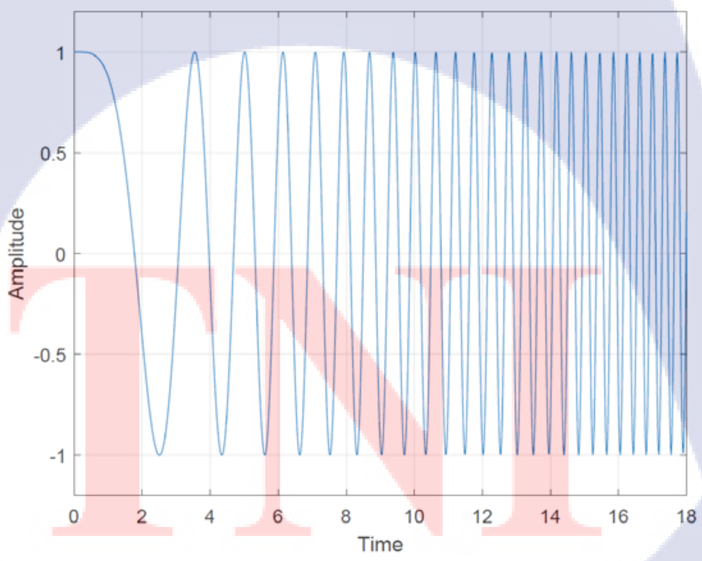


Figure 2.4. Visualization of the up-chirps used in the LoRa® modulation

2.1.1.2 Modulation

The key enabling factor in the LoRa® modulation standard. The LoRa® modulation uses a proprietary Chirp Spread Spectrum (CSS) scheme, which creates wideband linear frequency modulated chirps. The chip rate of these chirps are equal to the spectral bandwidth of the signal and uses 125, 250 or 500 kHz of bandwidth. The gains of using CSS are twofold, the first being that chirps are noise resistant and the second that these chirps can be generated with high precision using a cheap crystal, which leads to low chip costs. Because of the relative broadband characteristics of the chirps, multi-path fading is typically not an issue [4]. Doppler spread causes a frequency shift, which also only have a small effect on the channel thanks to the time-varying frequency of the chirps. as shown in Figure 2.4.

The frequency increases as a linear function of time using the LoRa® modulation, 15 km of range can be achieved in urban environment and up to 30 km with good line-of-sight. Additionally, LoRa® uses a Frequency-Hopping Spread Spectrum (FHSS) scheme to switch frequency between available channels according to a pseudo-random distribution. This helps to further mitigate interference.

A key thing to note with the CSS modulation scheme is that it produces a very sharp peak when auto-correlated, and has previously been deployed in radar applications [5]. The high peak helps to identify the correct time that the signal is received, and thus can be used to give a good estimate of the time it takes for a transmission to travel between two nodes.

2.1.1.3 Network Capacity

In order to make a long-range star network viable, the gateway must have a very high capacity or capability to receive messages from a very high volume of nodes. High network capacity in a LoRaWAN™ network is achieved by utilizing adaptive data rate and by using a multichannel multi-modem transceiver in the gateway so that simultaneous messages on multiple channels can be received. The critical factors effecting capacity are the number of concurrent channels, data rate (time on air), the payload length, and how often nodes transmit. Since LoRa® is a spread spectrum-based modulation, the signals are practically orthogonal to each other when different spreading factors are utilized. As the spreading factor changes, the effective data rate also changes. The gateway takes advantage of this property by being able to receive multiple different data rates on the same channel at the same time.

2.1.1.4 Device Classes

End-devices serve different applications and have different requirements. In order to optimize a variety of end application profiles, LoRaWAN™ utilizes different device classes. The device classes trade off network downlink communication latency versus battery lifetime. In a control or actuator-type application, the downlink communication latency is an important factor as can be seen in Figure 2.5.

Bi-directional end-devices (Class A): End-devices of Class A allow for bi-directional communications whereby each end-device's uplink transmission is followed by two short downlinks receive windows. The transmission slot scheduled by the end-device is based on its own communication needs with a small variation based on a random time basis (ALOHA-type of protocol). This Class A operation is the lowest power end-device system for applications that only require downlink communication from the server shortly after the end-device has sent an uplink transmission. Downlink communications from the server at any other time will have to wait until the next scheduled uplink.

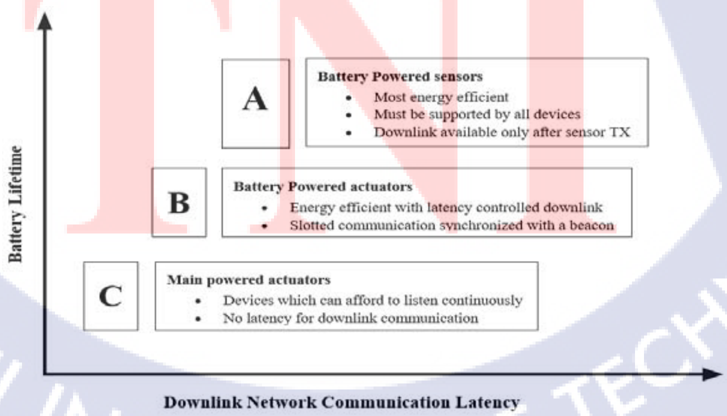


Figure 2.5 Device class of LoRa®

Class name	Intended usage
A (<< all >>)	**Battery powered sensors,** or actuators with no latency constraint Most energy efficient communication class. Must be supported by all devices
B (<< beacon >>)	**Battery powered actuators** Energy efficient communication class for latency controlled downlink. Based on slotted communication synchronized with a network beacon.
C (<<continuous>>)	**Mains powered actuators** Devices which can afford to listen continuously. No latency for downlink communication.

Figure 2.6 LoRaWAN communication profiles classes

Bi-directional end-devices with scheduled receive slots (Class B): In addition to the Class A random receive windows, Class B devices open extra receive windows at scheduled times. In order for the end-device to open it receive window at the scheduled time, it receives a time-synchronized beacon from the gateway. This allows the server to know when the end-device is listening as can be seen in Figure 2.6.

Bi-directional end-devices with maximal receive slots (Class C): End-devices of Class C have almost continuously open receive windows, only closed when transmitting.

Three different classes (A, B, C) of communication profiles are available in LoRa® networks between devices and applications. Each class serves different application needs and has optimized requirements for specific purposes. The key difference between A, B and C profiles is the trade-off made between latency and power consumption.

Class A

The below figure illustrates default configuration in LoRaWAN standard in SF12. Values can be adjusted.

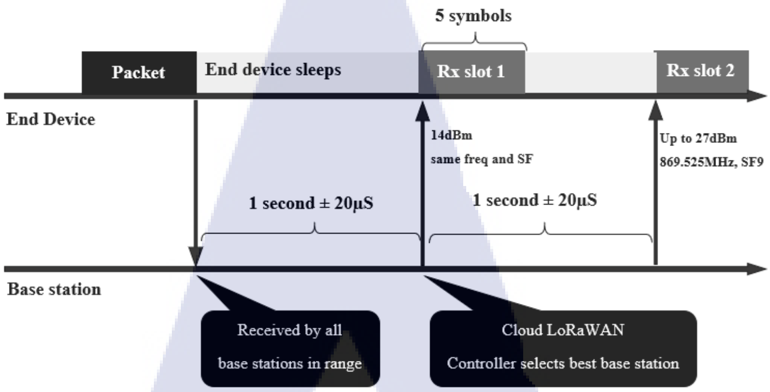


Figure 2.7 Class A default configuration profile

Class A devices implement a bi-directional communication profile whereby each end-device's uplink transmission is followed by two short downlinks receive windows. The transmission slot scheduled by the end-device is based on its own communication needs with a small variation based on a random time basis. This Class A operation is the lowest power consuming option for applications that only require downlink communication from the server shortly after the end-device has sent an uplink transmission. Downlink communications from the server at any other time has to wait until the next scheduled uplink. Class A covers the vast majority of use cases, and is the most power efficient mode of LoRa® as can be seen in Figure 2.7.

Class B

The below figure illustrates default configuration in LoRaWAN standard in SF12. Values can be adjusted.

Devices should implement a Class B communication profile when there is a requirement to ensure low latency of downlink communication, while keeping the power consumption as low as possible. Class B emulates a continuously receiving device by opening receive windows at fixed time intervals for the purpose of enabling server-initiated downlink messages.

LoRaWAN Class B option adds a synchronized reception window on the remote device. Class B is achieved by having the gateway send a beacon on a regular basis to synchronize all the end-point devices in the network. It allows devices to open a short extra reception window (called "ping slot") at a predictable time during a periodic time slot.

Class B is currently still in experimental status at the LoRa® alliance, but most use cases can already be covered by combination of class A and class C. For example, devices requiring periodic rendezvous points to receive configuration data (e.g. room reservation display) may periodically request time from the LPWA network, then synchronize their internal clock and periodically open rendezvous windows for downlink messages as can be seen in Figure 2.8.

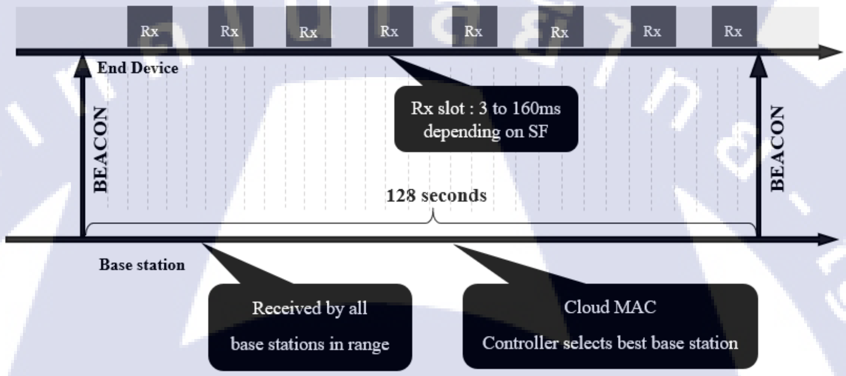


Figure 2.8 Class B default configuration profile

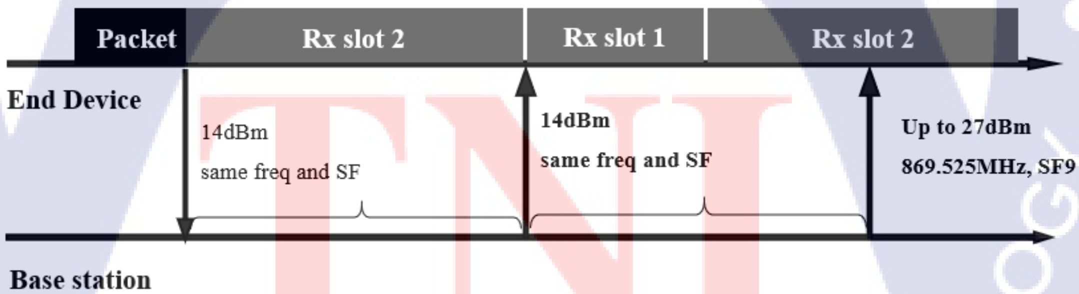


Figure 2.9 Class C default configuration profile

Class C

The below figure illustrates default configuration in LoRaWAN standard in SF12. Values can be adjusted.

Devices implementing Class C communication profiles are used for applications that have sufficient power available and thus do not need to minimize reception time windows. This is the case of most actuators (smart plugs, remote control of powered devices, etc.). Class C devices will listen with RX2 windows parameters as often as possible. The device listens on RX2 when it is not either (a) sending or (b) receiving on RX1, according to Class A definition. To do so, it will open a short window on RX2 parameters between the end of the uplink transmission and the beginning of the RX1 reception window and it will switch to RX2 reception parameters as soon as the RX1 reception window is closed; the RX2 reception window will remain open until the end-device has to send another message as can be seen in Figure 2.9.

2.1.1.5 Security

It is extremely important for any LPWAN to incorporate security. LoRaWAN™ utilizes two layers of security: one for the network and one for the application. The network security ensures authenticity of the node in the network while the application layer of security ensures the network operator does not have access to the end user's application data. AES encryption is used with the key exchange utilizing an IEEE EUI64 identifier. There are trade-offs in every technology choice but the LoRaWAN™ features in network architecture, device classes, security, scalability for capacity, and optimization for mobility address the widest variety of potential IoT applications.

2.1.1.6 Battery Lifetime

The nodes in a LoRaWAN™ network are asynchronous and communicate when they have data ready to send whether event-driven or scheduled. This type of protocol is typically referred to as the Aloha method. In a mesh network or with a synchronous network, such as cellular, the nodes frequently have to 'wake up' to synchronize with the network and check for messages. This synchronization consumes significant energy and is the number one driver of battery lifetime reduction. In a recent study and comparison done by GSMA of the various technologies addressing the LPWAN space, LoRaWAN™ showed a 3 to 5 times advantage compared to all other technology options.

2.1.1.7 Microcontroller

The Arduino Uno is a microcontroller board based on the ATmega328. It has 14 digital input/output pins, 6 analog inputs, a 16 MHz ceramic resonator, a USB connection, a power jack, an ICSP header, and a reset button. It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with a AC-to-DC adapter or battery to get started. The Uno differs from all preceding boards in that it does not use the FTDI USB-to-serial driver chip. Instead, it features the Atmega16U2 (Atmega8U2 up to version R2) programmed as a USB-to-serial converter as can be seen in Figure 2.10, Figure 2.11and Figure 2.12.

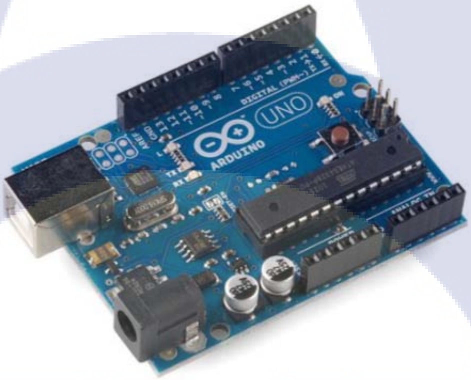


Figure 2.10 Arduino Uno board

Table 2.1 Arduino Uno Board Specification

Microcontroller	ATmega328
Operating Voltage	5V
Input Voltage (recommended)	7-12V
Input Voltage (limits)	6-20V
Digital I/O Pins	14 (of which 6 provide PWM output)
Analog Input Pins	6

Table 2.1 Arduino Uno Board Specification (Continued)

DC Current per I/O Pin	40 mA
DC Current for 3.3V Pin	50 mA
Flash Memory	32 KB (ATmega328) of which 0.5 KB used by bootloader
SRAM	2 KB (ATmega328)
EEPROM	1 KB (ATmega328)
Clock Speed	16 MHz

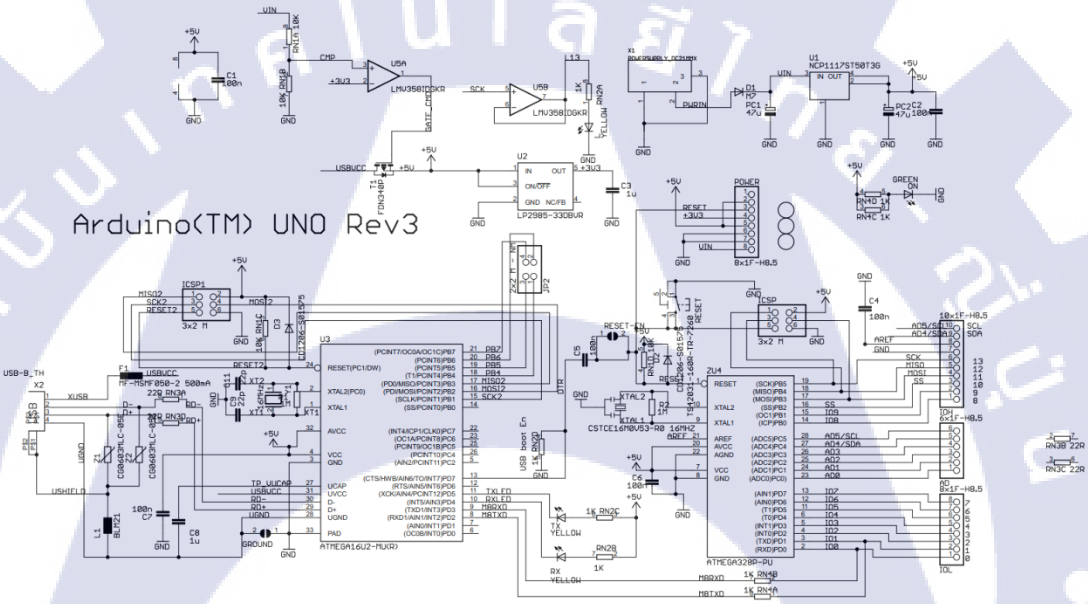


Figure 2.11 Schematic & Reference Design of Arduino Uno board

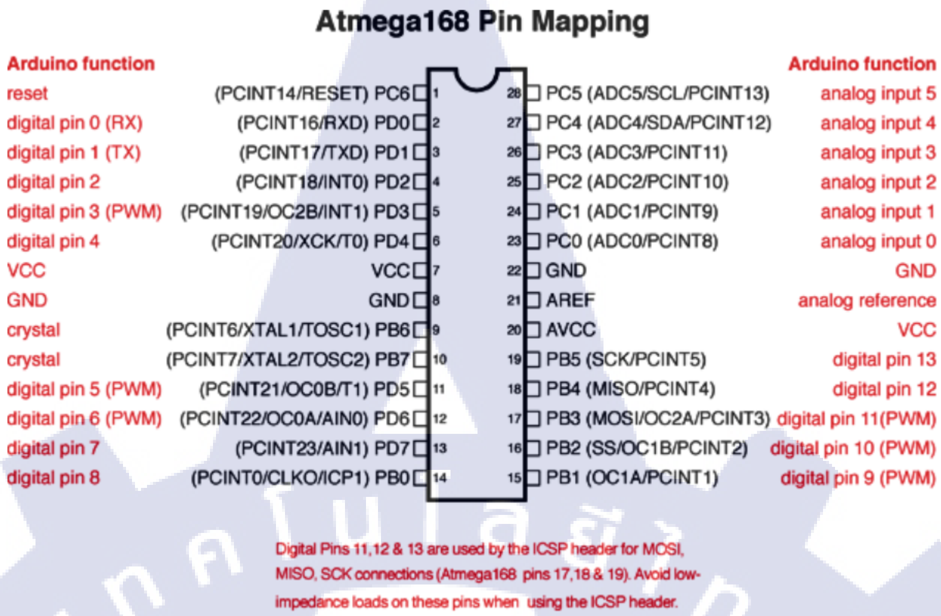


Figure 2.12 Atmega 168 pin mapping

2.1.1.8 Dipole Antenna and Radiation Pattern

A dipole antenna is a radio antenna that can be made of a simple wire, with a center fed driven element. It consists of two metal wire-rod conductors, in line with each other, with a small space between them. The radio frequency voltage is applied to the antenna at the center, between the two conductors. These antennas are the simplest practical antennas from a theoretical point of view.

The half-wave dipole antenna is the basis of many other antennas and is also used as a reference antenna for the measurement of antenna gain and radiated antenna density. At the frequency of resonance, i.e. at the frequency at which the length of the dipole equals a half-wavelength, we have a minimum voltage and a maximum current at the termination in the center of the antenna, as shown in Figure 2.13. The impedance is minimal. This is a simple antenna that radiates its energy out toward the horizon (perpendicular to the antenna). The resulting 3D pattern looks kind of like a donut or a bagel with the antenna sitting in the hole and radiating energy outward as can be seen in Figure 2.14. The strongest energy is radiated in the plane perpendicular to the antenna. The gain of the half-dipole is approximately 2.2 dBi.

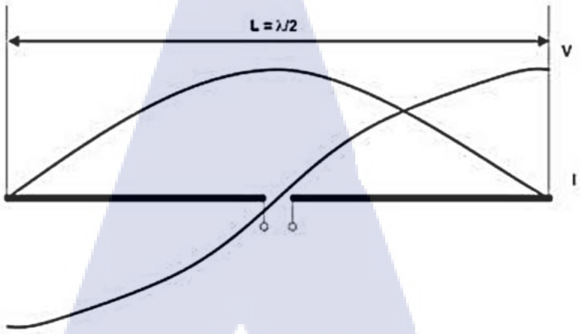


Figure 2.13 Half-wave dipole antenna voltage and current distribution

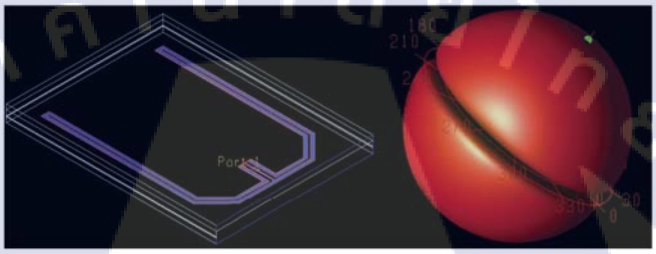


Figure 2.14 Half-wave dipole antenna model and radiation patterns

When the frequency is quite low, the wavelength becomes very long, so the half-wave dipole antenna is unpracticable. In this case a short dipole antenna can be used. The short dipole antenna is the simplest of all the antennas. It is an open circuited wire fed at its center. The word short always implies relative to a wavelength. So, the absolute size of the above dipole antenna does not matter, only the size of the wire relative to the wavelength of the frequency of the operation is important. Typically, a dipole is short if its length is less than a tenth of a wavelength. The directivity of the center fed short dipole antenna depends only on the sin of the polar angle component. It is calculated to be 1.76 dB, which is very low for realizable antennas. The polarization of the short dipole antenna is linear, as for all dipole type antennas. When evaluated in the x-y plane, this antenna is described as vertically polarized, because the Enfield is vertically oriented as can be seen in Figure 2.14.

2.1.1.9 Protocols

LoRaWAN is a MAC protocol, built to use the LoRa® physical layer. It is designed mainly for sensor networks, wherein sensors exchange packets with the server with a low data rate and relatively long-time intervals (one transmission per hour or even days). This section describes the LoRaWAN V1.0 specification, as released in January 2015.

Components of a LoRaWAN Network Several components of the network are defined in the LoRaWAN specification and are required to form a LoRaWAN network: end-devices, gateways and the network server.

End-device: the low-power consumption sensors that communicate with gateways using LoRa®.

Gateway: the intermediate devices that forward packets coming from end-devices to a network server over an IP backhaul interface allowing a bigger throughput, such as Ethernet or 3G. There can be multiple gateways in a LoRa® deployment, and the same data packet can be received by more than one gateway.

Network server: responsible for de-duplicating and decoding the packets sent by the devices and generating the packets that should be sent back to the devices.

Unlike traditional cellular networks, the end-devices are not associated with a particular gateway in order to have access to the network. The gateways serve simply as a link layer relay and forward the packet received from the end-devices to the network server after adding information regarding the reception quality. Thus, an end-device is associated with a network server, which is responsible for detecting duplicate packets, choosing the appropriate gateway for sending a reply (if any), consequently for sending back packets to the end-devices. Logically, gateways are transparent to the end-devices.

A LoRa® frame begins with a preamble. The preamble starts with a sequence of constant upchirps that cover the whole frequency band. The last two upchirps encode the sync word. The sync word is a one-byte value that is used to differentiate LoRa® networks that use the same frequency bands. A device configured with a given sync word will stop listening to a transmission if the decoded sync word does not match its configuration. The sync word is followed by two and a quarter downchirps, for a duration of 2.25 symbols. The total duration of this preamble can be configured between 10.25 and 65,539.25 symbols. The structure of the preamble can be seen in Figure 2.15.

After the preamble, there is an optional header. When it is present, this header is transmitted with a code rate of 4/8. This indicates the size of the payload, the code rate used for the end of the transmission and whether or not a 16-bit CRCfor the payload is present at the end of the frame. The header also includes a CRC to allow the receiver to discard packets with invalid headers. The payload size is stored using one byte, limiting the size of the payload to 255 bytes. The header is optional to allow disabling it in situations where it is not necessary, for instance when the payload length, coding rate and CRC presence are known in advance. The payload is sent after the header, and at the end of the frame is the optional CRC. A schematic summarizing the frame format can be seen in Figure 2.16.

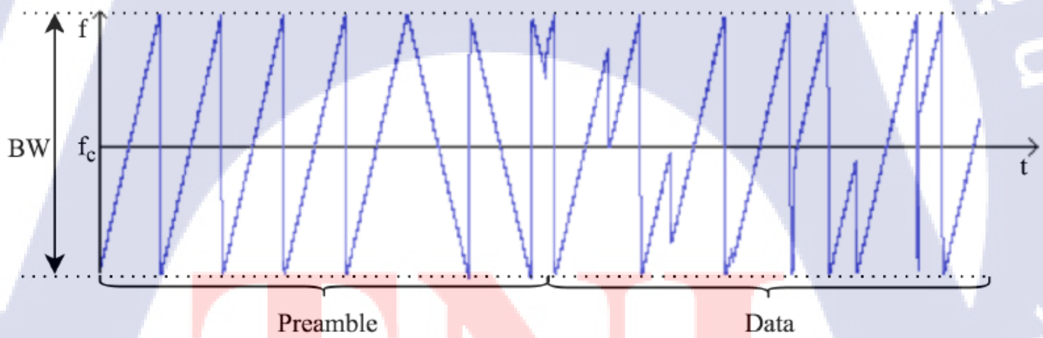


Figure 2.15 Frequency variation over time of a sample signal emitted by a LoRa® transmitter

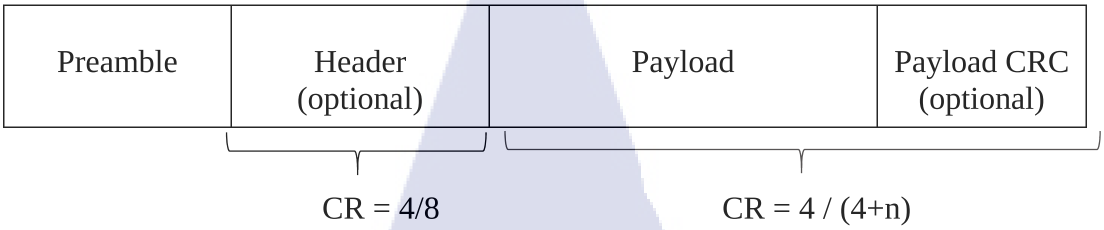


Figure 2.16 Structure of a LoRa® frame

Equation (1), derived from Semtech's datasheets [6,7,8], gives the number of symbols required to transmit a payload ns, as a function of all of these parameters. This number should be added to the number of symbols of the preamble, in order to compute the total size of the packet in symbols. In this equation, PL is the payload size in bytes, CRC is 16 if the CRC is enabled and zero otherwise, H is 20 when the header is enabled and zero otherwise and DE is two when the low data rate optimization is enabled and zero otherwise. This equation also shows that the minimum size of a packet is eight symbols.

$$n_s = 8 + \max\left(\left\lceil \frac{8PL - 4SF + 8 + CRC + H}{4 \times (SF - DE)} \right\rceil \times \frac{4}{CR}, 0\right) \qquad (2.1)$$

The header and CRC are mandatory for uplink messages, which makes it impossible to use a spreading factor of six in LoRaWAN. Downlink messages have the header, but not the CRC. The code rate that should be used is not specified and neither is when the end-devices should use the low data rate optimization.

The message format is detailed in Figure 2.17. DevAddr is the short address of the device. FPort is a multiplexing port field. The value zero means that the payload contains only MAC commands. When this is the case, the FOptsLen field must be zero. FCnt is a frame counter. MIC is a cryptographic message integrity code, computed over the fields MHDR, FHDR, FPort and the encrypted FRMPayload. MType is the message type, indicating among other things whether it is an uplink or a downlink message and whether or not it is a confirmed message. Acknowledgments are requested for confirmed messages. Major is the LoRaWAN version; currently, only a value of zero is valid. ADR and ADRAckReq control the data rate adaptation mechanism by the network server. ACK acknowledges the last received frame. FPending indicates that the network server has additional data to send and that the end-device should send another frame as soon as possible so that it opens receive windows. FOptsLen is the length of the FOpts field in bytes. FOpts is used to piggyback MAC commands on a data message. CID is the MAC command identifier, and Args are the optional arguments of the command. FRMPayload is the payload, which is encrypted using AES with a key length of 128 bits. The minimal size of the MAC header is 13 bytes; its maximal size is 28 bytes. Knowing this, it is possible to compute the maximum channel capacity available for application data payloads with

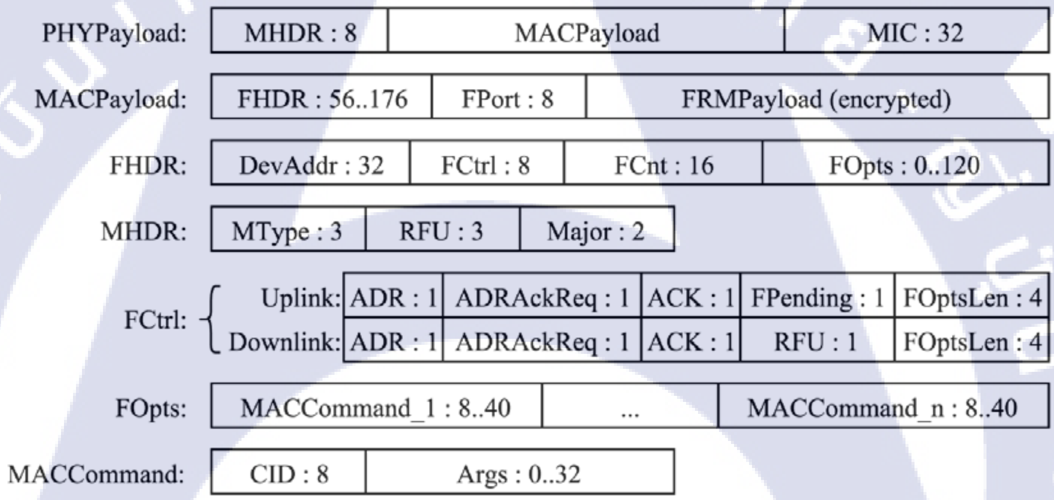


Figure 2.17 LoRaWAN frame format. The sizes of the fields are in bits

given modulation parameters thanks to Equations (1). As packets are sent from a device to the network server and vice versa, there is no destination address on uplink packets, and there is no source address on downlink packets.

LoRaWAN MAC Commands LoRaWAN defines many MAC commands that allow customizing end-device parameters [9]. One of them, LinkCheckReq, can be sent by an end-device to test its connectivity. All of the others are sent by the network server. These commands can control the data rate and output power used by the device, as well as the number of times each unconfirmed packet should be sent, the global duty cycle of the device, changing parameters of the receive windows and changing the channels used by the device. One command is used to query the battery level and reception quality of a device.

2.1.1.10 Technical Comparisons

Table 2 that the cellular-based indoor localization relies on the mobile cellular network, remarkably the wireless telephone technology Global System Mobile (GSM) communication. Such cellular-based system generally estimates mobile user position in building with low accuracy, but power consumption is relatively high and the signal strength is based on a cell site under the main infrastructure. Consequently, indoor localization based on cellular network has received less attention than those of non-cellular based systems.

It is also seen in Table 1 that the Radio Frequency Identification (FID), which operates at a frequency 13.6 MHz, has been recognized as one of a potential technology for locating objects or people. RFID typically enables a one-way communication via noncontact and advanced automatic identification through radio signals. RFID consumes low power, and has widely been utilized a wide range of applications such as automobile assembly industry, warehouse management, supply chain network. However, RFID provides low data transfer rate and operates in a short range lower than one meter, a number of RFID tags is required and a complicated network is ultimately required to be designed properly. Alternatively, Bluetooth, Wi-Fi, and ZigBee technologies that operate at 2.4 GHz with different protocols have also been utilized for indoor localization.

Bluetooth offers information exchange between devices with high security, low cost, low power, and small size. However, device discovery procedure is reiterated in each location finding, resulting in the increase in localization latency and power consumption and leading unsuitable for real-time operations. The Wi-Fi-Based localization system is one of the most widespread approaches for indoor localization due to the fact that Wi-Fi is embedded in most mobile devices without installing extra software or manipulating the hardware.

The drawback of Wi-Fi-Based localization system is reliance on Wi-Fi location in building and signal attenuation caused by the static environment or movement of furniture and doors, resulting in low-accuracy localization. ZigBee is another wireless technology standard which provides short and medium range communications with low-power consumption but do not require large data throughput. Although it is possible for a communication distance of 100 m. for Line-of-Sight operation, the coverage range for in indoor environments could possibly be only 20m -30m due to obstacles in static indoor environment. As ZigBee operates in the unlicensed ISM bands, it is therefore relatively vulnerable to interference from a wide range of signal types using the same frequency which can disrupt radio communications. In summary, several techniques for the enhancement of indoor localization based on such Bluetooth, Wi-Fi, and ZigBee technologies have been proposed in order to increase accuracy and precision, coverage and resolution, latency, and effects of random errors caused by signal interference and reflections [8]. As a consequence, a hybrid positioning system, which is defined as systems for determining the location by combining several different wireless technologies, have been suggested as an alternative solution for indoor localization quality enhancement [9].

Table 2.2 Comparisons of Technical Specifications on Rf-Based Communication Technology for Indoor Localization

Specifications	**(i) Cellular Communications**	**(ii) Non-Cellular (Ad-Hoc and Peer-to-Peer Communications)**					
		RFID	**Bluetooth**	**Wi-Fi**	**ZigBee**	**UWB**	**LoRa**
1. Standard	GSM/GPRS	IEEE 802.15.1	IEEE 802.15.1	IEEE 802.11n	IEEE 802.15.4	IEEE 802.15.6	**LoRaWAN**
2. Operating Frequency	900/1800 MHz	13.56 MHz	2.4 GHz	2.4/5 GHz	2.4 GHz	3.1GHz-10.6GHz	**430/433/ 868/915 MHz**
3. Maximum Distance	30km (LR)	1m (SR)	30m (MR)	50m (MR)	100m (MR)	10m (SR)	**5km(UA), 15km(SA), (LR)**
4. Data Rate Transfer	10 Mbps (High)	50 Mbps (Low)	1-3 Mbps (Medium)	54 Mbps (High)	250 kbps (Low)	55-410 Mbps (High)	**50 kbps (Low)**
5. Transmission Current (mA)	500-1000 mA (High)	15 mA (Low)	35 mA (Low)	238 mA (High)	32 mA (Low)	55 c mA (Medium)	**25 mA (Low)**
6. Operation Time 2000-mAh Battery	2-4 Hr. (SOT)	133 Hr. (LOT)	57 Hr. (LOT)	8.4 Hr. (SOT)	62 Hr. (LOT)	36 Hr. (LOT)	**80 Hr. (LOT)**

Table 2.3 Summary of LoRa® Communication Performance Configuration in Fine-Tune Physical Layer

Configurable Setting	Values	Effects
1. Bandwidth	125…500 kHz	Higher bandwidths allow for transmitting packets at higher data rates (1 kHz = 1 kbps), but reduce receiver sensitivity and communication range.
2. Spreading Factor	$2^6 \ldots 2^{12} \frac{\text{Chips}}{\text{Symbol}}$	Bigger spreading factors increase the signal-to-noise ratio and hence radio sensitivity, augmenting the communication range at the cost of longer packets and hence a higher energy expenditure.
3. Coding Rate	4/5…4/8	Larger coding rate increase the resilience to interference bursts and decoding error at the cost of longer packets and higher energy expenditure.
4. Transmission Power	-4…20 dBm	Higher transmission powers reduce the signal-to-noise ratio at the cost of an increase in the energy consumption of the transmitter.

Recently, LoRa®, which stands for "Long Range", is a promising long-range wireless communications system, fostered by the LoRa® Alliance [10]. LoRa® has been designed as a long-lived battery-powered device, where the energy consumption is of paramount importance. Typically, LoRa® can be distinctly classified into two layers: (i) a physical layer using the Chirp Spread Spectrum (CSS) radio modulation technique and (ii) a MAC layer protocol (LoRaWAN). The LoRa® physical layer, developed by Semtech, allows for long-range, low-power and low-throughput communications. It operates on the 433-, 868- or 915-MHz ISM bands, depending on the region in which it is deployed. The payload of each transmission can range from 2–255 octets, and the data rate can reach up to 50 Kbps when channel aggregation is employed. The modulation technique is a proprietary technology from Semtech. LoRaWAN provides a medium access control mechanism, enabling many end-devices to communicate with a gateway using the LoRa® modulation. While the LoRa® modulation is proprietary, the LoRaWAN is an open standard being developed by the LoRa® Alliance.

2.1.2 Indoor Localization Methods

2.1.2.1 Indoor Positioning Fundamentals

Prior to the development of modern positioning technology, various physical “signs” were used to obtain position information. An animal in a forest might leave an odor marking, for example, for use in recognizing an approximate location later on. It has long been common for man to use the positions of stars and the earth’s magnetic field in order to establish directions and thereby estimate their locations. The evolution of such “signs” is an important driving force in the development of positioning technology. GPS using Radio Frequency (RF) technology have achieved great success for outdoor localization. Precise inertial measurement devices, such as accelerometers and gyroscopes, allow missile and airplanes to localize themselves and navigate accurately. Indoors, wireless information access is now widely available, including RF signals, light and sound waves, etc., which can be explored to make location estimates in indoor environments. Micro-Electro-Mechanical System (MEMS) inertial sensors are today incorporated into tiny chips that can be integrated into the smart devices that are so popular nowadays. The main driving force behind these developments is the advancement in technologies such as wireless communication and miniature electronics allowing a panoply of exciting developments within the last decade.

Location estimation techniques differ Enormously depending on the kind of technologies used and measurements made. The major location estimation algorithm types are: triangulation, proximity, fingerprinting, and dead reckoning; while possible measured quantities include time of flight (TOF), angle of arrival (AOA), RSS, link quality, sensor readings, and the like. Many challenges are still to be faced in the adaptation of these technologies for particular situations. ANN algorithms have their unique advantages and disadvantages for particular application scenarios. This leads to suppose that combining more than one type of complementary positioning technique could provide better performance, which is, of course, what is actually observed in most modern localization systems.

Better performance is the constant pursuit of the thesis, and is also an urgent need for many location-based applications and services, particularly for indoor applications. Accuracy might be the most important performance indicator of such a system, while meanwhile other parameters, such as coverage, complexity, robustness and cost also need to be considered. Indoor and outdoor environments are of course fundamentally deferent, which influences in a crucial way the adoption of particular localization solutions for indoor environments.

2.1.2.2 Received Signal Strength Indication (RSSI)

Equation (2), The received signal strength (RSS) based approach is one of the simplest and widely used approaches for indoor localization [10] – [14]. The RSS is the actual signal power strength received at the receiver, usually measured in decibel-milliwatts (dBm) or milliwatts (mW). The RSS can be used to estimate the distance between a transmitter (Tx) and a receiver (Rx) device; the higher the RSS value the smaller the distance between Tx and Rx. The absolute distance can be estimated using a number of different signal propagation models given that the transmission power or the power at a reference point is known. RSSI (which is often confused with RSS) is the RSS indicator, a relative measurement of the RSS that has arbitrary units and is mostly defined by each chip vendor. For instance, the Atheros Wi-Fi chipset uses RSSI values between 0 and 60, while Cisco uses a range between 0 and 100. Using the RSSI and a simple path-loss propagation model [15], the distance d between Tx and Rx can be estimated from (2.2) as

$$RSSI = -10n \log_{10}(d) + A \qquad (2.2)$$

where n is the path loss exponent (which varies from 2 in free space to 4 in indoor environments) and A is the RSSI value at a reference distance from the receiver. RSS based localization, in the DBL case, requires trilateration or N-point literation, i.e., the RSS at the device is used to estimate the absolute distance between the user device and at least three reference points; then basic geometry/trigonometry is applied for the user device to obtain its location relative to the reference points as shown in Figure 2.18. In a similar manner, in the MBL case, the RSS at the reference points is used to obtain the position of the user device. In the latter case, a central controller or ad-hoc communication between anchor points is needed for the total RSS collection and processing. On the other hand, RSS based proximity-based services (such as sending marketing alerts to a user when in the vicinity of a retail store), require a single reference node to create a geofence 3 and estimate the proximity of the user to the anchor node using the path loss estimated distance from the reference point.

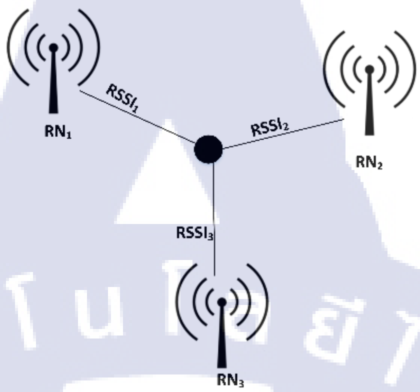


Figure 2.18 RSSI based localization

While the RSS based approach is simple and cost efficient, it suffers from poor localization accuracy (especially in non-line of-sight conditions) due to additional signal attenuation resulting from transmission through walls and other big obstacles and severe RSS fluctuation due to multipath fading and indoor noise [10], [16]. Different filters or averaging mechanisms can be used to mitigate these effects. However, it is unlikely to obtain high localization.

2.1.2.3 Time of Arrival

Time of Arrival is the process of determining distance from the time a transmission takes from anchor node to target node. In theory this is a straight forward procedure since the speed of light is well known. The distance between two nodes are calculated from the time difference between transmitting and receiving, and as a result the position can be determined by trilateration in the same way as in the RSS case. However, in practice, this becomes a lot harder due to clock drifts. Essentially the problem comes down to clock synchronization, where nodes need to be synchronized down to nanosecond scale in order to achieve a proper distance approximation. For a network such as Lora® WAN where the nodes are supposed to be low-cost and idle for a large amount of the time, the internal clock drift makes this a quite hard problem. There are techniques to go about this, such as two-way time of arrival (TW-TOA) or time difference of arrival (TDOA). The common denominator of these techniques is that they only demand the anchor nodes to be time synchronized, and there for the low cost of target nodes is not compromised. In TW-TOA the round-trip time between anchor and target node is measured, and if the target node has a well-defined processing time of the message this can give a good distance estimation. For TDOA the target node sends a broadcast message which is received by multiple anchor nodes. The anchor nodes, which are time synchronized, can then calculate the distance from the difference in time between signal receptions. This is a multiliterate problem which involves solving a set of hyperbolic functions, and therefore an additional anchor node is needed compared to the trilateration case.

2.1.2.4 Time of Flight (ToF) Technique

Time of Flight (ToF) exploits the signal propagation time to calculate the distance between the transmitter Tx and the receiver Rx. The ToF value multiplied by the speed of light c = 3 x 108 m/sec Provides the physical distance between Tx and Rx. In Figure 2.19, the ToF from three different reference nodes is used to estimate the distances between the reference nodes and the device. Basic geometry can be used to calculate the location of the device with respect to the access points. Similar to the RSS, the ToF values can be used in both the DBL and MBL scenarios. ToF requires strict synchronization between transmitters and receivers and, in many cases, timestamps to be transmitted with the signal (depending on the underlying communication protocol). The key factors that affect ToF estimation accuracy are the signal bandwidth and the sampling rate. Low sampling rate (in time) reduces the ToF resolution since the signal may arrive between the sampled intervals. Frequency domain superresolution techniques are commonly used to obtain the ToF with high resolution from the channel frequency response. In multipath indoor environments, the larger the bandwidth,

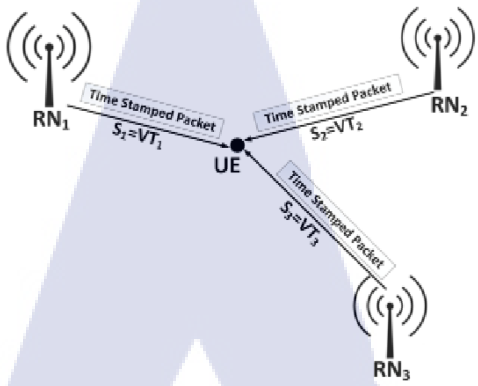


Figure 2.19 ToF based user equipment (UE) localization

The higher the resolution of ToF estimation. Although largeband width and super-resolution techniques can improve the performance of ToF, still they cannot eliminate significant localization errors when the direct line of sight path between the transmitter and receiver is not available. This is because the obstacles deflect the emitted signals, which then traverse through a longer path causing an increase in the time taken for the signal to propagate from Tx to Rx. Let t1 be the time when Tx i sends a message to the Rx j that receives it at t2 where t2 = t1 + tp (tp is the time taken by the signal to traverse from Tx to Rx) [17]. So, the distance between the i and j can be calculated using Equation (2.3) where v is the signal velocity.

$$Dij = (t2 - t1) \div \times v \tag{2.3}$$

2.1.2.5 Time Difference of Arrival (TDoA) Technique

Time Difference of Arrival (TDoA) exploits the difference in signals propagation times from different transmitters, measured at the receiver. This is different from the ToF technique, where the absolute signal propagation time is used. The TDoA measurements (TD(i;j) - from transmitters i and j) are converted into physical distance values LD(i;j) = c _ TD(i;j), where c is the speed of light. The receiver is now located on the hyperboloid given by Eq. (2.4).

$$L_{D(i,j)} = \sqrt{(X_i - x)^2 + (Y_i - y)^2 + (Z_i - z)^2} - \sqrt{(X_i - x)^2 + (Y_i - y)^2 + (Z_i - z)^2} \qquad (2.4)$$

where (Xi; Yi; Zi) are the coordinates of the transmitter/reference node i and (x; y; z) are the coordinates of the receiver/user.

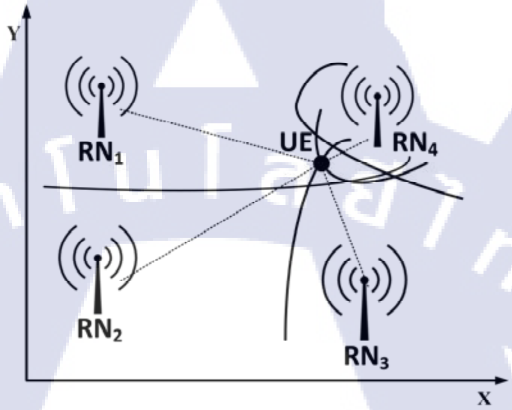


Figure 2.20 TDoA based localization and proximity detection

The TDoA from at least three transmitters is needed to calculate the exact location of the receiver as the intersection of the three (or more) hyperboloids. The system of hyperbola equations can be solved either through linear regression [18] or by linearizing the equation using Taylorseries expansion. Figure 2.20 shows how four different RNs can be used to obtain the 2D location of any target. Figure shows the hyperbolas formed as a result of the measurements obtained from the RNs to obtain the user location (black dot). The TDoA estimation accuracy depends (similar to the ToF techniques) on the signal bandwidth, sampling rate at the receiver and the existence of direct line of sight between the transmitters and the receiver. Strict synchronization is also required, but unlike ToF techniques where synchronization is needed between the transmitter and the receiver, in the TDoA case only synchronization between the transmitters is required.

2.1.2.6 Angle of Arrival (AOA) Technique

Angle of Arrival (AoA) based approaches use antennae arrays [19] (at the receiver side) to estimate the angle at which the transmitted signal impinges on the receiver by exploiting and calculating the time difference of arrival at individual elements of the antennae array. The main advantage of AoA is that the device/user location can be estimated with as low as two monitors in a 2D environment, or three monitors in a 3D environment respectively. Although AoA can provide accurate estimation when the transmitter-receiver distance is small, it requires more complex hardware and careful calibration compared to RSS techniques, while its accuracy deteriorates with increase in the transmitter-receiver distance where a slight error in the angle of arrival calculation is translated into a huge error in the actual location estimation [20]. Moreover, due to multipath effects in indoor environments the AoA in terms of line of sight (LOS) is often hard to obtain. Figure 2.21 shows how AoA can be used to estimate the user location (as the angles at which the signals are received by the antenna array can help locate the user device.).

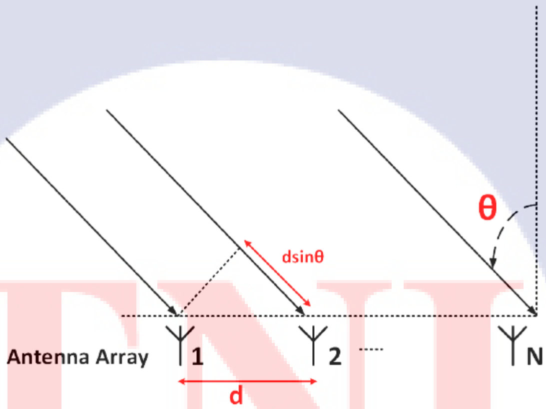


Figure 2.21 AoA based localization

In the AOA technique, the estimation of the signal reception angles, from at least two sources, is compared with either the signal amplitude or carrier phase across multiple antennas. The location can be found from the intersection of the angle line for each signal source, see Figure 2.22. AOA estimation algorithms are very sensitive to many factors, which may cause errors in their estimation of target position. Furthermore, AOA estimation algorithms have a higher complexity compared to other methods. For instance, the antenna array geometry has a major role in the estimation algorithm. Increasing the distance between the sender and receiver may decrease the accuracy. The AOA technique can be used with other techniques to increase its accuracy.

AOA based algorithms have been used in a vast amount of literature. Xu et al., presented a new cooperative positioning method based on AOA that utilizes pairwise AOA information among all the sensor nodes rather than relying only on anchor nodes [21]. Lee proposed the use of a signal model and weighted-average to estimate AOA parameters for low data rate UWB (LR-UWB) [22]. A Kalman filter based AOA estimation algorithm was introduced by Subramanian, that relies on a new linear quadratic frequency domain invariant beamforming strategy [23]. Furthermore, many studies have been conducted to evaluate the performance of AOA for different applications, environments, hardware, and configurations. Mok et al., studied the feasibility and performance of AOA for UWB in the Ubisense Real-Time Location System (RTLS) when integrated with GPS to facilitate resource management in underground railway construction sites [24]. The influence of UWB directional antennas on the performance of AOA estimation was analyzed in detail by Gerok et al. [25] who presented a corrected AOA estimation algorithm that mitigates the error resulting from the UWB directional antenna.

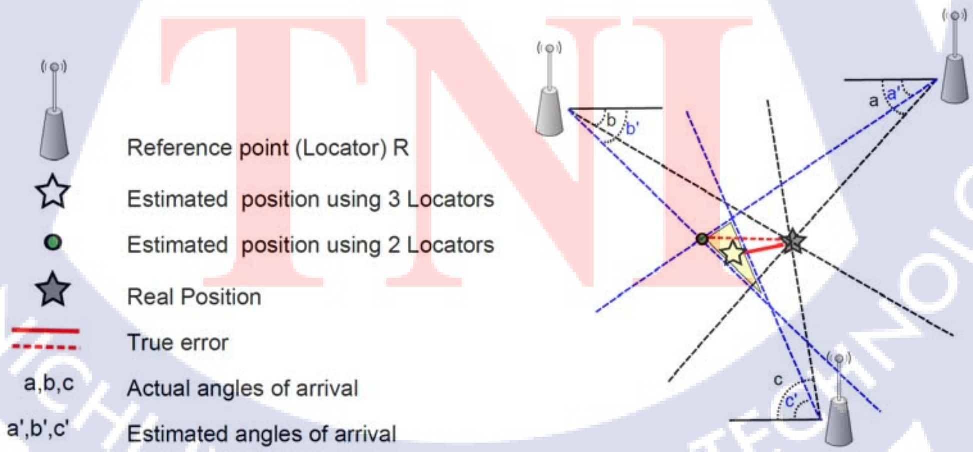


Figure 2.22 Angle of arrival (AOA)-based algorithms

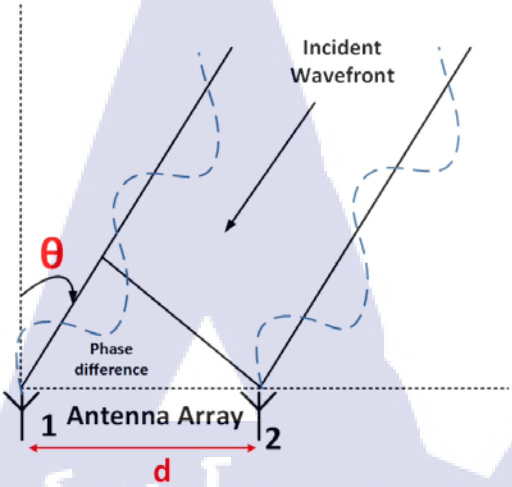


Figure 2.23 PoA based localization

2.1.2.7 Phase-of-Arrival (PoA)

PoA based approaches use the phase or phase difference of carrier signal to estimate the distance between the transmitter and the receiver. A common assumption for determining the phase of signal at receiver side is that the signals transmitted from the anchor nodes (in DBL), or user device (in MBL) are of pure sinusoidal form having same frequency and zero phase offset. There are a number of techniques available to estimate the range or distance between the Tx and Rx using PoA. One technique is to assume that there exists a finite transit delay Di between the Tx and Rx, which can be expressed as a fraction of the signal wavelength. As seen in Figure 2.23, the incident signals arrive with a phase difference at different antenna in the antenna array, which can be used to obtain the use location. A detailed discussion on PoA-based range estimation is beyond the scope of the paper. Therefore, interested readers are referred to [26], [27]. Following range estimation, algorithms used for ToF can be used to estimate user location. If the phase difference between two signals transmitted from different anchor points is used to estimate the distance, TDoA based algorithms can be used for localization. PoA can be used in conjunction with RSSI, ToF, TDoA to improve the localization accuracy and enhance the performance of the system. The problem with PoA based approach is that it requires line-of sight for high accuracy, which is rarely the case in indoor environments.

Table 2.4 provides a summary of the discussed techniques for indoor localization and discusses the advantages and disadvantages of these techniques. Interested readers are referred to [17] for detailed discussion on these localization techniques.

Table 2.4 Advantages and Disadvantages of Different Localization Techniques

Technique	Advantages	Disadvantages
RSSI	Easy to implement, cost efficient, can be used with a number of technologies	Prone to multipath fading and environmental noise, lower localization accuracy, can require fingerprinting
CSI	More robust to multipath and indoor noise.	It is not easily available on off-the-shelf NICs
AoA	Can provide high localization accuracy, does not require any fingerprinting	Might require directional antennas and complex hardware, requires comparatively complex algorithms and performance deteriorates with increase in distance between the transmitter and receiver
ToF	Provides high localization accuracy, does not require any fingerprinting	Requires time synchronization between the transmitters and receivers, might require time stamps and multiple antennas at the transmitter and receiver. Line of Sight is mandatory for accurate performance.
TDoA	Does not require any fingerprinting, does not require clock synchronization among the device and RN	Requires clock synchronization among the RNs, might require time stamps, requires larger bandwidth
RToF	Does not require any fingerprinting, can provide high localization accuracy	Requires clock synchronization, processing delay can affect performance in short ranger measurements
PoA	Can be used in conjunction with RSS, ToA, TDoA to improve the overall localization accuracy	Degraded performance in the absence of line of sight
Fingerprinting	Fairly easy to use	New fingerprints are required even when there is a minor variation in the space

2.1.2.8 Return Time of Flight (RToF) Technique

RToF measures the round-trip (i.e., transmitter-receiver transmitter) signal propagation time to estimate the distance between Tx and Rx [17]. The ranging mechanisms for both ToF and RToF are similar; upon receiving a signal from the transmitter, the receiver responds back to the transmitter, which then calculates the total round-trip ToF. The main benefit of RToF is that a relatively moderate clock synchronization between the Tx and the Rx is required, in comparison to ToF. However, RToF estimation accuracy is affected by the same factors as ToF (i.e., sampling rate and signal bandwidth) which in this case is more severe since the signal is transmitted and received twice. Another significant problem with RToF based systems is the response delay at the receiver which highly depends on the receiver electronics and protocol overheads. The latter one can be neglected if the propagation time between the transmitter and receiver is large compared to the response time, however the delay cannot be ignored in short range systems such as those used for indoor localization. Let t1 be the time when Tx i sends a message to the Rx j that receives it at t2 where t2 = t1 + tp. j, at time t3, transmits a signal back to i that receives it at t4 So the distance between the i and j can be calculated using Equation (2.5) [17].

$$D_{ij} = \frac{(t_4 - t_1) - (t_3 - t_2)}{2} \times v \tag{2.5}$$

2.1.3 Artificial Neural Network

An Artificial Neural Network (ANN) is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. Basic building block of every artificial neural network is artificial neuron, that is, a simple mathematical model (function). Such a model has three simple sets of rules: multiplication, summation and activation. At the entrance of artificial neuron, the inputs are weighted what means that every input value is multiplied with individual weight. In the middle section of artificial neuron is sum function that sums all weighted inputs and bias. At the exit of artificial neuron, the sum of previously weighted inputs and bias is passing through activation function that is also called transfer function as can be seen in Figure 2.24.

Although the working principles and simple set of rules of artificial neuron looks like nothing special the full potential and calculation power of these models come to life when we start to interconnect them into artificial neural networks.

These artificial neural networks use simple fact that complexity can grow out of merely few basic and simple rules as can be seen in Figure 2.25.

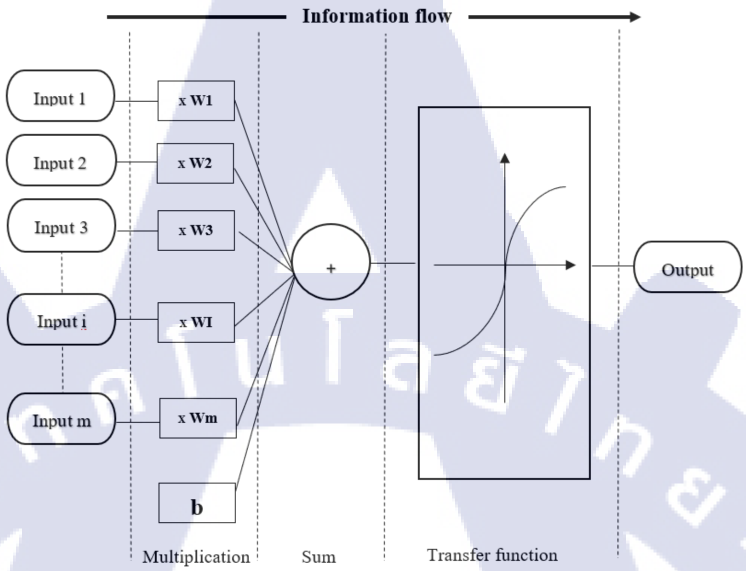


Figure 2.24 Working principle of an artificial neuron

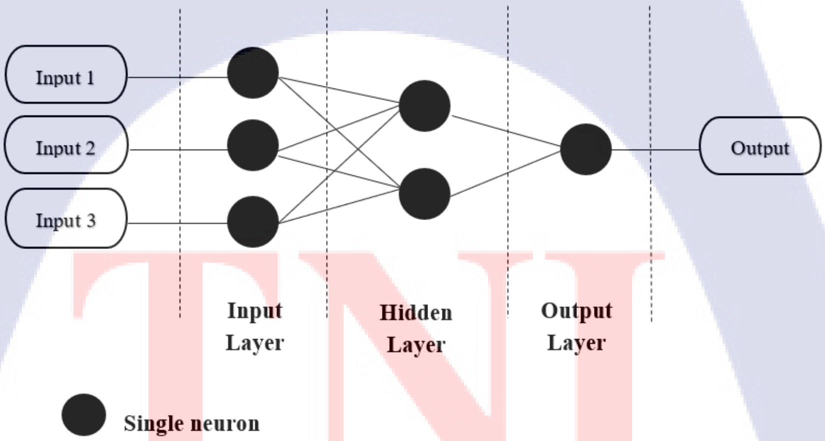


Figure 2.25 Example of simple artificial neural network

In order to fully harvest the benefits of mathematical complexity that can be achieved through interconnection of individual artificial neurons and not just making system complex and unmanageable we usually do not interconnect these artificial neurons randomly. In the past,thesis have come up with several “standardized” topographies of artificial neural networks. These predefined topographies can help us with easier, faster and more efficient problem solving. Different types of artificial neural network topographies are suited for solving different types of problems.

After determining the type of given problem, we need to decide for topology of artificial neural network we are going to use and then fine-tune it. We need to fine-tune the topology itself and its parameters. Fine-tuned topology of artificial neural network does not mean that we can start using our artificial neural network, it is only a precondition. Before we can use our artificial neural network, we need to teach it solving the type of given problem. Just as biological neural networks can learn their behavior/responses on the basis of inputs that they get from their environment the artificial neural networks can do the same. There are three major learning paradigms: supervised learning, unsupervised learning and reinforcement learning. We choose learning paradigm similar as we chose artificial neuron network topography-based on the problem we are trying to solve. Although learning paradigms are different in their principles they all have one thing in common; on the basis of “learning data” and “learning rules” (chosen cost function) artificial neural network is trying to achieve proper output response in accordance to input signals.

2.1.3.1 Artificial neuron

Artificial neuron is a basic building block of every artificial neural network. Its design and functionalities are derived from observation of a biological neuron that is basic building block of biological neural networks (systems) which includes the brain, spinal cord and peripheral ganglia. Similarities in design and functionalities can be seen in Fig.32. where the left side of a figure represents a biological neuron with its soma, dendrites and axon and where the right side of a figure represents an artificial neuron with its inputs, weights, transfer function, bias and outputs.

In case of biological neuron information comes into the neuron via dendrite, soma processes the information and passes it on via axon. In case of artificial neuron, the information comes into the body of an artificial neuron via inputs that are weighted (each input can be individually multiplied with a weight). The body of an artificial neuron then sums the weighted inputs, bias and "processes" the sum with a transfer function. At the end an artificial neuron passes the processed information via output(s). Benefit of artificial neuron model simplicity can be seen in its mathematical description below.

$$y(k) = F(\sum_{i=0}^{m} w_i(k) \cdot x_i(k) + b) \qquad (2.6)$$

Where:

- Xi(k) is input value in discrete time k where i goes from 0 to m,
- Wi(k) is weight value in discrete time k where i goes from 0 to m,
- b is bias,
- F is a transfer function,
- Yi(k) is output value in discrete time k.

As seen from a model of an artificial neuron and its equation (2.6) the major unknown variable of our model is its transfer function. Transfer function defines the properties of artificial neuron and can be any mathematical function. We choose it on the basis of problem that artificial neuron (artificial neural network) needs to solve and in most cases, we choose it from the following set of functions: Step function, Linear function and Non-linear (Sigmoid) function. Step function is binary function that has only two possible output values. That means if input value meets specific threshold the output value results in one value and if specific threshold is not meet that results in different output value. Situation can be described with equation (2.7).

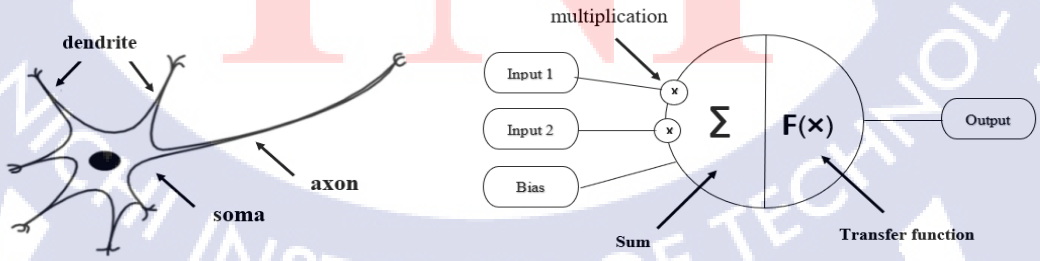


Figure 2.26 Biological and artificial neuron design

$$y = \begin{cases} 1 \text{ if } w_i x_i & \geq \text{threshold} \\ 0 \text{ if } w_i x_i & < \text{threshold} \end{cases} \tag{2.7}$$

When this type of transfer function is used in artificial neuron we call this artificial neuron perceptron. Perceptron is used for solving classification problems and as such it can be most commonly found in the last layer of artificial neural networks. In case of linear transfer function artificial neuron is doing simple linear transformation over the sum of weighted inputs and bias. Such an artificial neuron is in contrast to perceptron most commonly used in the input layer of artificial neural networks. When we use non-linear function, the sigmoid function is the most commonly used. Sigmoid function has easily calculated derivate, which can be important when calculating weight updates in the artificial neural network as can be seen in Figure 2.26.

2.1.3.2 Artificial Neural Networks

When combining two or more artificial neurons we are getting an artificial neural network. If single artificial neuron has almost no usefulness in solving real-life problems the artificial neural networks have it. In fact, artificial neural networks are capable of solving complex real-life problems by processing information in their basic building blocks (artificial neurons) in a non-linear, distributed, parallel and local way.

The way that individual artificial neurons are interconnected is called topology, architecture or graph of an artificial neural network. The fact that interconnection can be done in numerous ways results in numerous possible topologies that are divided into two basic classes. Fig. 32. shows these two topologies; the left side of the figure represent simple feedforward topology (acyclic graph) where information flows from inputs to outputs in only one direction and the right side of the figure represent simple recurrent topology (semiacyclic graph) where some of the information flows not only in one direction from input to output but also in opposite direction. While observing need to mention that for easier handling and mathematical describing of an artificial neural network we group individual neurons in layers. On Figure 2.27. can see input, hidden and output layer.

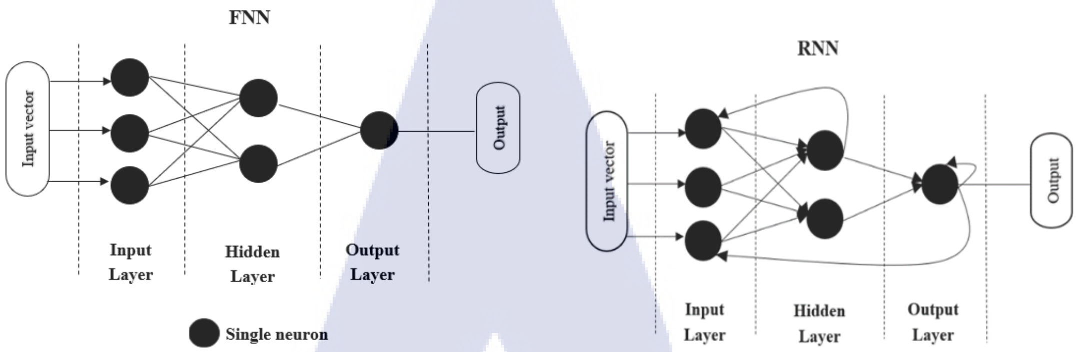


Figure 2.27 Feed-forward (FNN) and recurrent (RNN) topology of an artificial neural network

When choose and build topology of our artificial neural network we only finished half of the task before we can use this artificial neural network for solving given problem. Just as biological neural networks need to learn their proper responses to the given inputs from the environment the artificial neural networks need to do the same. So, the next step is to learn proper response of an artificial neural network and this can be achieved through learning (supervised, un-supervised or reinforcement learning). No matter which method we use, the task of learning is to set the values of weight and biases on basis of learning data to minimize the chosen cost function.

2.1.3.3 Feed-forward Artificial Neural Networks

Artificial neural network with feed-forward topology is called Feed-Forward artificial neural network and as such has only one condition: information must flow from input to output in only one direction with no back-loops. There are no limitations on number of layers, type of transfer function used in individual artificial neuron or number of connections between individual artificial neurons. The simplest feed-forward artificial neural network is a single perceptron that is only capable of learning linear separable problems. Simple multi-layer feed-forward artificial neural network for purpose of analytical description as can be seen in Figure 2.28.

$$
\begin{aligned}
n_1 &= F_1(w_1x_1 + b_1) \\
n_2 &= F_2(w_2x_2 + b_2) \\
n_3 &= F_2(w_2x_2 + b_2) \\
n_4 &= F_3(w_3x_3 + b_3)
\end{aligned} \tag{2.8}
$$

$$
\begin{aligned}
m_1 &= F_4(q_1n_1 + q_2n_2 + b_4) \\
m_2 &= F_5(q_3n_3 + q_4n_4 + b_5)
\end{aligned} \tag{2.9}
$$

$$
y = F_6\begin{bmatrix} r_1\big(F_4\big[q_1F_1[w_1x_1 + b_1] + q_2F_2[w_2x_2 + b_2]\big] + b_4\big) + \cdots \\ \ldots + r_2(F_5[q_3F_2[w_2x_2 + b_2] + q_4F_3[w_3x_3 + b_3] + b_5]) + \ b_6 \end{bmatrix} \tag{2.10}
$$

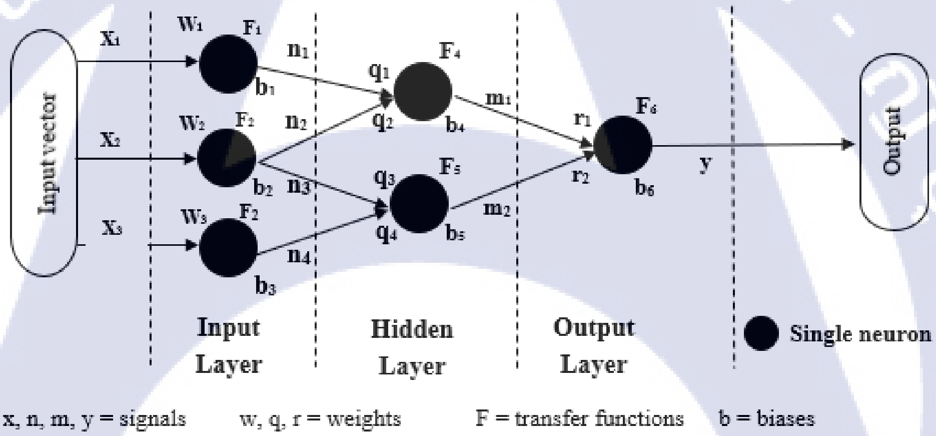


Figure 2.28 Feed-forward artificial neural network

As corresponding analytical description with sets of equations (2.8), (2.9) and (2.10) the simple feed-forward artificial neural network can led to relatively long mathematical descriptions where artificial neural networks' parameters optimization problem solving by hand is impractical. Although analytical description can be used on any complex artificial neural network in practice we use computers and specialized software that can help us build, mathematically describe and optimize any type of artificial neural network.

2.1.3.4 Recurrent Artificial Neural Networks

Artificial neural network with the recurrent topology is called Recurrent artificial neural network. It is similar to feed-forward neural network with no limitations regarding back loops. In these cases, information is no longer transmitted only in one direction but it is also transmitted backwards. This creates an internal state of the network which allows it to exhibit dynamic temporal behavior. Recurrent artificial neural networks can use their internal memory to process any sequence of inputs. Figure 2.29 shows small Fully Recurrent

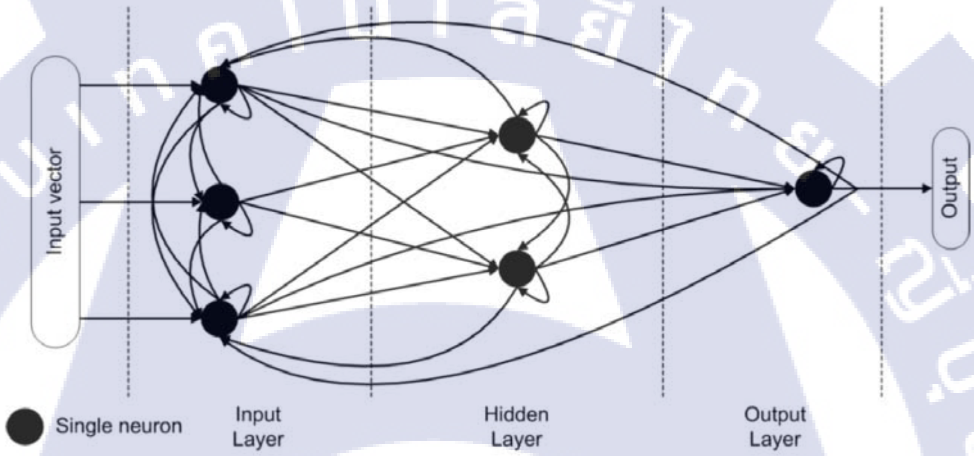


Figure 2.29 Fully recurrent artificial neural network

artificial neural network and complexity of its artificial neuron interconnections. The most basic topology of recurrent artificial neural network is fully recurrent artificial network where every basic building block (artificial neuron) is directly connected to every other basic building block in all direction. Other recurrent artificial neural networks such as Hopfield, Elman, Jordan, bi-directional and other networks are just special cases of recurrent artificial neural networks.

2.1.3.5 Elman and Jordan Artificial Neural Networks

Elman network also referred as Simple Recurrent Network is special case of recurrent artificial neural networks. It differs from conventional two-layer networks in that the first layer has a recurrent connection. It is a simple three-layer artificial neural network that has back-loop from hidden layer to input layer trough so called context unit This type of artificial neural network has memory that allowing it to both detect and generate time-varying patterns as can be seen in Figure 2.30.

The Elman artificial neural network has typically sigmoid artificial neurons in its hidden layer, and linear artificial neurons in its output layer. This combination of artificial neurons transfer functions can approximate any function with arbitrary accuracy if only there is enough artificial neurons in hidden layer. Being able to store information Elman artificial neural network is capable of generating temporal patterns as well as spatial patterns and responding on them. Jordan network is similar to Elman network. The only difference is that context units are fed from the output layer instead of the hidden layer as can be seen in Figure 2.31.

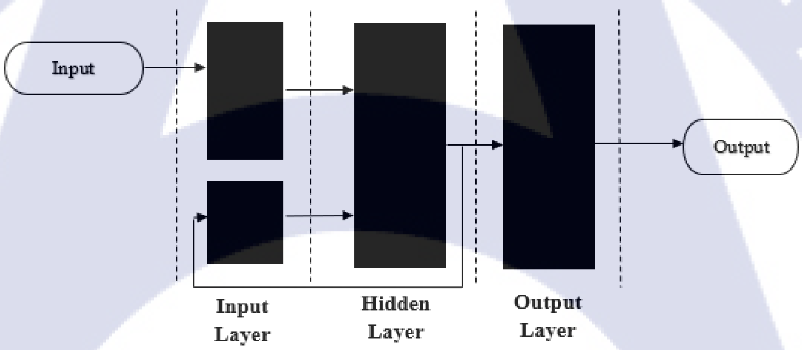


Figure 2.30 Elman artificial neural network

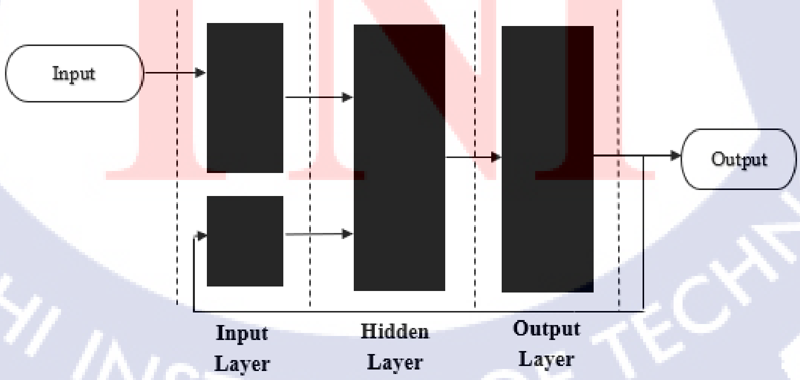


Figure 2.31 Jordan artificial neural network

2.1.3.6 Long Short-Term Memory

Long Short-Term Memory is one of the recurrent artificial neural network's topologies. In contrast with basic recurrent artificial neural networks it can learn from its experience to process, classify and predict time series with very long-time lags of unknown size between important events. This makes Long Short-Term Memory to outperform other recurrent artificial neural networks, Hidden Markov Models and other sequence learning methods.

Long Short-Term Memory artificial neural network is build from Long Short-Term Memory blocks that are capable of remembering value for any length of time. This is achieved with gates that determine when the input is significant enough remembering it, when continue to remembering or forgetting it, and when to output the value. Architecture of Long Short-Term Memory block is shown in Figure 2.32 where input layer consists of sigmoid units. Top neuron in the input layer process input value that might be sent to a memory unit depends on computed value of second neuron from the top in the input layer. The third neuron from the top in the input layer decide how long will memory unit hold (remember) its value and the bottom most neuron determines when value from memory should be released to the output. Neurons in first hidden layer and in output layer are doing simple multiplication of their inputs and a neuron in the second hidden layer computes simple linear function of its inputs. Output of the second hidden layer is fed back into input and first hidden layer in order to help making decisions.

2.1.3.7 Bi-directional Artificial Neural Networks (Bi-ANN)

Bi-directional artificial neural networks are designed to predict complex time series. They consist of two individual interconnected artificial neural (sub) networks that performs direct and inverse (bidirectional) transformation. Interconnection of artificial neural sub networks is done through two dynamic artificial neurons that are capable of remembering their internal states. This type of interconnection between future and past values of the processed signals increase time series prediction capabilities. As such these artificial neural networks not only predict future values of input data but also past values. That brings need for two phase learning; in first phase we teach one artificial neural sub network for predicting future and in the second phase we teach a second artificial neural sub network for predicting past as can be seen in Figure 2.33.

2.1.3.8 Self-Organizing Map (SOM)

Self-organizing map is an artificial neural network that is related to feed-forward networks but it needs to be told that this type of architecture is fundamentally different in arrangement of neurons and motivation. Common arrangement of neurons is in a hexagonal or rectangular grid. Self-organizing map is different in comparison to other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space. They use unsupervised learning paradigm to produce a low-dimensional, discrete representation of the input space of the training samples, called a map what makes them especially useful for visualizing low-dimensional views of high-dimensional data. Such networks can learn to detect regularities and correlations in their input and adapt their future responses to that input accordingly as can be seen in Figure 2.34.

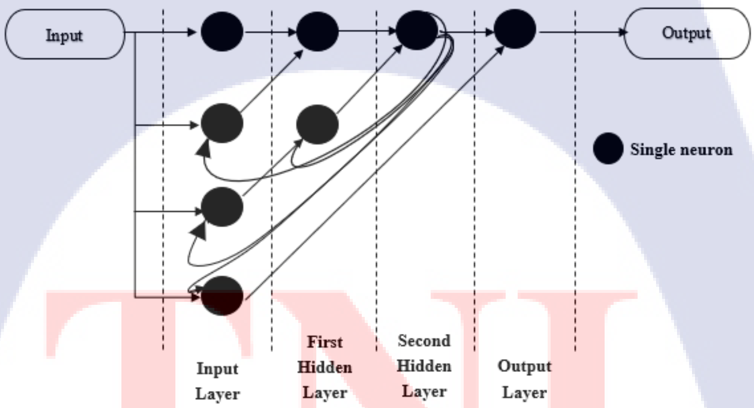


Figure 2.32 Simple Long Short-Term Memory artificial neural network (block)

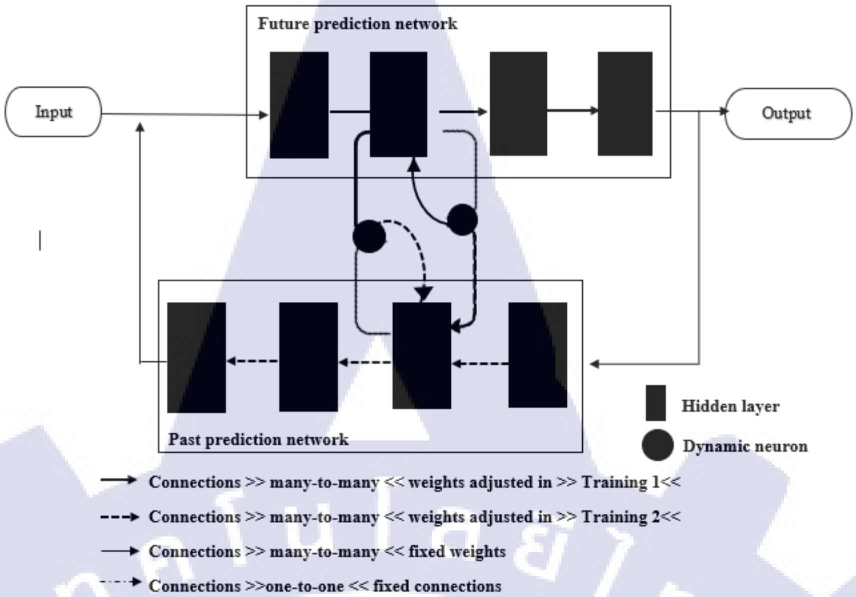


Figure 2.33 Bi-directional artificial neural network

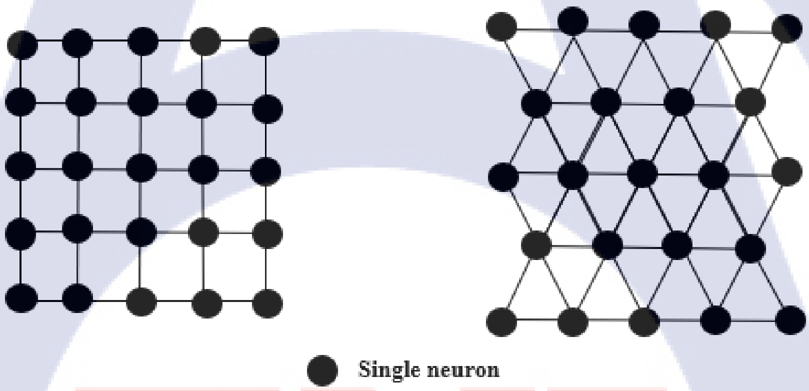


Figure 2.34 Self-organizing Map in rectangular (left) and hexagonal (right) grid

Just as others artificial neural networks need learning before they can be used the same goes for self-organizing map; where the goal of learning is to cause different parts of the artificial neural network to respond similarly to certain input patterns. While adjusting the weights of the neurons in the process of learning they are initialized either to small random values or sampled evenly from the subspace spanned by the two largest principal component eigenvectors. After initialization artificial neural network needs to be fed with large number of example vectors. At that time Euclidean distance to all weight vectors is computed and the neuron with weight vector most similar to the input is called the best matching unit. The weights of the best matching unit and neurons close to it are adjusted towards the input vector. This process is repeated for each input vector for a number of cycles. After learning phase, we do so-called mapping (usage of artificial neural network) and during this phase the only one neuron whose weight vector lies closest to the input vector will be winning neuron. Distance between input and weight vector is again determined by calculating the Euclidean distance between them.

2.1.3.9 Stochastic Artificial Neural Network

Stochastic artificial neural networks are a type of an artificial intelligence tool. They are built by introducing random variations into the network, either by giving the network's neurons stochastic transfer functions, or by giving them stochastic weights. This makes them useful tools for optimization problems, since the random fluctuations help it escape from local minima. Stochastic neural networks that are built by using stochastic transfer functions are often called Boltzmann machine.

2.1.3.10 Physical Artificial Neural Network

Most of the artificial neural networks today are software-based but that does not exclude the possibility to create them with physical elements which base on adjustable electrical current resistance materials. History of physical artificial neural networks goes back in 1960’s when first physical artificial neural networks were created with memory transistors called memristors. Memristors emulate synapses of artificial neurons. Although these artificial neural networks were commercialized they did not last for long due to their incapability for scalability. After this attempt several others followed such as attempt to create physical artificial neural network based on nanotechnology or phase change material.

2.1.4 Learning

There are three major learning paradigms; supervised learning, unsupervised learning and reinforcement learning. Usually they can be employed by any given type of artificial neural network architecture. Each learning paradigm has many training algorithms.

2.1.4.1 Supervised learning

Supervised learning is a machine learning technique that sets parameters of an artificial neural network from training data. The task of the learning artificial neural network is to set the value of its parameters for any valid input value after having seen output value. The training data consist of pairs of input and desired output values that are traditionally represented in data vectors. Supervised learning can also be referred as classification, where we have a wide range of classifiers, each with its strengths and weaknesses. Choosing a suitable classifier (Multilayer perceptron, Support Vector Machines, k-nearest neighbor algorithm, Gaussian mixture model, Gaussian, naive Bayes, decision tree, radial basis function classifiers,) for a given problem is however still more an art than a science. In order to solve a given problem of supervised learning various steps has to be considered. In the first step we have to determine the type of training examples. In the second step we need to gather a training data set that satisfactory describe a given problem. In the third step we need to describe gathered training data set in form understandable to a chosen artificial neural network. In the fourth step we do the learning and after the learning we can test the performance of learned artificial neural network with the test (validation) data set. Test data set consist of data that has not been introduced to artificial neural network while learning.

2.1.4.2 Unsupervised learning

Unsupervised learning is a machine learning technique that sets parameters of an artificial neural network based on given data and a cost function which is to be minimized. Cost function can be any function and it is determined by the task formulation. Unsupervised learning is mostly used in applications that fall within the domain of estimation problems such as statistical modelling, compression, filtering, blind source separation and clustering. In unsupervised learning we seek to determine how the data is organized. It differs from supervised learning and reinforcement learning in that the artificial neural network is given only unlabeled examples. One common form of unsupervised learning is clustering where we try to categorize data in different clusters by their similarity. Among above described artificial neural network models, the Self-organizing maps are the ones that the most commonly use unsupervised learning algorithms.

2.1.4.3 Reinforcement learning

Reinforcement learning is a machine learning technique that sets parameters of an artificial neural network, where data is usually not given, but generated by interactions with the environment. Reinforcement learning is concerned with how an artificial neural network ought to take actions in an environment so as to maximize some notion of long-term reward. Reinforcement learning is frequently used as a part of artificial neural network's overall learning algorithm.

After return function that needs to be maximized is defined, reinforcement learning uses several algorithms to find the policy which produces the maximum return. Naive brute force algorithm in first step calculates return function for each possible policy and chooses the policy with the largest return. Obvious weakness of this algorithm is in case of extremely large or even infinite number of possible policies. This weakness can be overcome by value function approaches or direct policy estimation. Value function approaches attempt to find a policy that maximizes the return by maintaining a set of estimates of expected returns for one policy; usually either the current or the optimal estimates. These methods converge to the correct estimates for a fixed policy and can also be used to find the optimal policy. Similar as value function approaches the direct policy estimation can also find the optimal policy. It can find it by searching it directly in policy space what greatly increases the computational cost.

Reinforcement learning is particularly suited to problems which include a long-term versus short-term reward trade-off. It has been applied successfully to various problems, including robot control, telecommunications, and games such as chess and other sequential decision-making tasks.

2.1.4.4 Usage of Artificial Neural Networks

One of the greatest advantages of artificial neural networks is their capability to learn from their environment. Learning from the environment comes useful in applications where complexity of the environment (data or task) make implementations of other type of solutions impractical. As such artificial neural networks can be used for variety of tasks like classification, function approximation, data processing, filtering, clustering, compression, robotics, regulations, decision making, etc.

Choosing the right artificial neural network topology depends on the type of the application and data representation of a given problem. When choosing and using artificial neural networks we need to be familiar with theory of artificial neural network models and learning algorithms. Complexity of the chosen model is crucial; using to simple model for specific task usually results in poor or wrong results and over complex model for a specific task can lead to problems in the process of learning.

Complex model and simple task results in memorizing and not learning. There are many learning algorithms with numerous tradeoffs between them and almost all are suitable for any type of artificial neural network model. Choosing the right learning algorithm for a given task takes a lot of experiences and experimentation on given problem and data set. When artificial neural network model and learning algorithm is properly selected we get robust tool for solving given problem.

2.2 Literature Reviews

Various indoor positioning technologies can be used concurrently to gain the advantages of each one. The appropriate indoor positioning technology should be selected carefully in order to make the right balance between the complexity and the performance of IPSs [28,29]. Indoor positioning technologies are classified by researchers in many different ways. In 2003, Collin et al., classified indoor positioning technologies into two classes according to the need for hardware: technologies that require special hardware in the building and self-contained technologies [30]. On the other hand, Gu et al., provided different classifications of indoor positioning technologies in 2009, in which they divided them, into two classes based on their need for existence of networks: network-based

In 2011, Al Nuaimi and Kamel classified indoor positioning technologies into fixed indoor positioning systems and indoor pedestrian positioning systems [31]. This classification is quite similar to the classification introduced by Collin et al., Similarly, Chliz et al., classified the indoor positioning techniques into two categories; parametric where a position is computed based on prior knowledge and non-parametric where a position is computed by processing the data taking into consideration some statistical parameters [32].

On the other hand, Rainer Mautz provided a different classification of indoor positioning technologies in 2012 [33]. He divided them into thirteen categories; camera, infrared, tactile polar systems, sound, WLAN and WiFi, RFID, ultra-wideband, high sensitivity GNSS, pseudofiles, other radio frequencies, inertial navigation, magnetic systems, and infrastructure systems. Table 5 summarizes existing classification of indoor positioning technologies gathered from the literature. Table 2.5 Different Classifications of Indoor Positioning Technologies.

Table 2.5 Different Classifications of Indoor Positioning Technologies

Author-Year	**Classified based on**	**Categories**
Collin et al.—2003	Need for hardware	Technologies that require hardware in the building, and self-contained ones
Gu et al.—2009	Existence of network	Network-based and non-network-based technologies
	System architecture	Self-positioning architecture, self-oriented infrastructure-assisted architecture, and infrastructure positioning architecture
	Main medium used to determine positions	Ultrasound, radio frequency, magnetic, vision-Based, and audible sound technologies
Al Nuaimi and Kamel—2011	Installed system in a building	Fixed indoor positioning and indoor pedestrian positioning
Chliz et al.—2011	Prior knowledge	Parametric and non-parametric technologies
Rainer Mautz—2012	Sensor type	Camera, infrared, tactile & polar systems, sound, WLAN and Wi-Fi, RFID, ultra-wideband, high sensitivity GNSS, pseudofiles, other radio frequencies, inertial navigation, magnetic systems, and infrastructure systems

In contrast to the previous classifications, we provide a new classification for indoor positioning technologies according to the infrastructure of the system that uses them, see Figure 3. We classify indoor positioning technologies into two main classes; building dependent and building independent. Building dependent indoor positioning technologies refer to technologies that depend on the building that they will operate in. They depend either on an existing technology in the building or on the map and structure of the building. Building dependent indoor positioning technologies can be further divided into two major classes: indoor positioning technologies that require dedicated infrastructure and indoor positioning technologies that utilize the building's infrastructure. The need for dedicated infrastructure is determined according to the general structure of most current buildings; e.g., most buildings contain WIFI while almost none contains radio frequency identification. Indoor positioning technologies that require dedicated infrastructure are radio frequency that is either RFID or UWB, infrared, ultrasonic, Zigbee and laser

Indoor positioning technologies that utilize the building's infrastructure are WIFI, cellular based, and Bluetooth. On the other hand, the building independent technologies do not require any special hardware in a building such as dead reckoning and image-based technologies. In dead reckoning, an object can determine its current position by knowing its past position, its speed and the direction in which it is moving [34]. Image based technologies mainly rely on a camera sensor and image processing). Image based technologies can be building independent or building dependent. Image based building dependent technologies depend on special signs in a building or a map of the building. Image based building independent technologies do not require information about the building's map or any special signs. Figure 2.35 shows our classification of indoor positioning technologies according to the infrastructure of the system that uses them. Further detail of each technology is given in the following section.

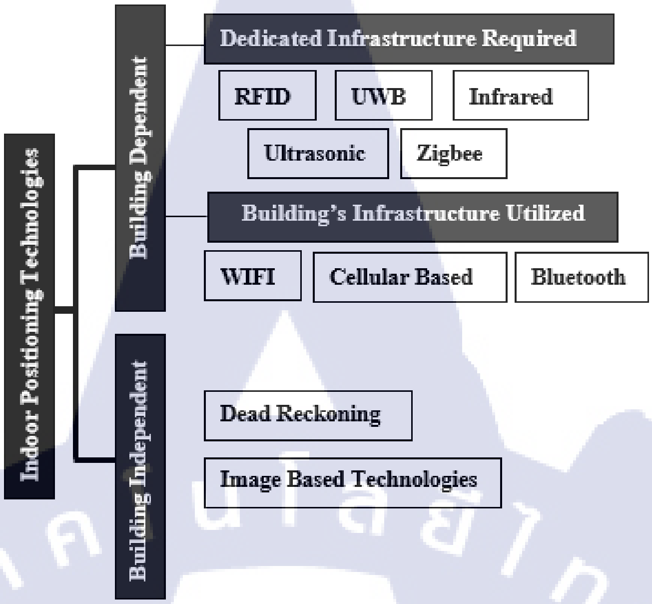


Figure 2.35 Classification of indoor positioning technologies

Radio Frequency Identification (RFID). Radio frequency Identification uses radio waves to transmit the identity of an object (or person) wirelessly. RFID technology is most commonly used to automatically identify objects in large systems. It is based on exchanging different frequencies of radio signals between two main components: readers and tags. Tags emit radio signals that are received by readers and vice versa. Both tags and readers use predefined radio frequencies and protocols to send and receive data between them. Tags are attached to all the objects that need to be tracked. The tags consist of a microchip which can typically store up to 2 kilobytes of data, and a radio antenna. There are two types of tags; active tags and passive tags. On the other hand, an RFID reader consists of different components; including an antenna, transceiver, power supply, processor, and interface, in order to connect to a server [34,35,36]. Although different positioning methods can be used with RFID, proximity is the most used one and it senses the presence of RFID tags rather than the exact position [32,35,37]. Also received signal strength (RSS) could be used with RFID [35].

Ultra-Wideband (UWB). The Federal Communications Commission defines UWB as an RF signal occupying a portion of the frequency spectrum that is greater than 20% of the center carrier frequency, or has a bandwidth greater than 500 MHz UWB is a communication channel that spreads information out over a wide portion of the frequency spectrum. This allows UWB transmitters to transmit large amounts of data while consuming little transmit energy [36]. UWB can be used for positioning by utilizing the time difference of arrival (TDOA) of the RF signals to obtain the distance between the reference point and the target [38].

Infrared (IR). Infrared wireless communication makes use of the invisible spectrum of light just below the red edge of the visible spectrum, which makes this technology less intrusive than indoor positioning that is based on visible light [33,37]. IR can be used in two different ways; direct IR and diffuse IR. Infrared Data Association (IrDA) is an example of direct IR that uses a point-to-point ad-hoc data transmission standard designed for very low-power communications. IrDA requires line of sight communication between devices over a very short distance and up to 16 Mbps. On the other hand, diffuse IR has stronger signals than direct IR, and therefore it has a longer reach (9–12 m). Diffuse IR uses wide angle LEDs which emit signals in many directions. Thus, it allows one to many connections and does not require direct line of sight [36]. Proximity, differential phase-shift, and angle of arrival (AoA) positioning methods are frequently used with Infrared technology [39-41].

Ultrasonic. An ultrasound wave is “a mechanical wave that is an oscillation of pressure transmitted through a medium” [36]. It does not interfere with electromagnetic waves and has relatively short range. Ultrasonic positioning systems leverage building material and the air as a propagation medium. The relative distance between the different devices can be estimated using time of arrival (ToA) measurements of ultrasound pulses traveling from emitters to the receivers. The emitter’s coordinates can be estimated by multilateration from three (or more) ranges to some fixed receivers [33].

Zigbee. The ZigBee standard “provides network, security, and application support services operating on top of the IEEE 802.15.4 specification” It is a short distance and low rate wireless personal area network [33,38]. A basic ZigBee node is small and has low complexity and cost. It consists of a microcontroller and a multichannel two-way radio on one piece of silicon [36]. Zigbee is designed for applications that require low power consumption and low data throughput There are two different physical device types used for ZigBee nodes, full function device (FFD) and reduced function device (RFD) [36]. This technology achieves positioning by coordination and communications with neighboring nodes. Usually, RSS values are used to estimate a distance between Zigbee nodes [33]. Phase shift measurement is a new approach that was recently introduced to ranging the nodes in ZigBee network [40,41]. The phase shift of the reflected signal from the target node due to the time delay between the target and transmitter is used to measure the distance between them.

Wireless Local Area Network (WLAN). The IEEE 802.11WLANstandard was ratified in June 1997. The standard defines “the protocol and compatible interconnection of data communication equipment via the air in a local area network (LAN) using the carrier sense multiple access protocol with collision avoidance (CSMA/CA) medium sharing mechanism” [36]. Using a typical gross bit rate of 11, 54, or 108 Mbps and a range of 50 to 100 m, IEEE 802.11 is considered the dominant local wireless networking standard [35]. Using WiFi in indoor positioning and navigation systems depends on knowing a list of wireless routers that are available in an area in which the system operates. The most popular WLAN positioning method is received signal strength (RSS) which is easy to extract in 802.11 networks and could run on off-the-shelf WLAN hardware [33]. Time of arrival (ToA), time difference of arrival (TDoA), and angle of arrival (AoA) mechanisms are less common in WLAN because of the angular measurements and time delay complexity. Using RSS, the accuracy of WLAN positioning systems is around 3 to 30 m [42-44].

Cellular Based. Global System for Mobile Communications (GSM) networks are available in most countries and can outreach the coverage of WLAN with lower positioning accuracy. GSM operates in the licensed bands and prevents interference from other devices operating at a similar frequency (unlike WLAN) [33]. It is possible to use indoor positioning on a mobile cellular network if the building is covered by one or more base stations with strong RSS [35]. The most common method of GSM indoor positioning is fingerprinting which is based on the power level (RSS) [33].

Bluetooth. Bluetooth is a proprietary format managed by the Bluetooth Special Interest Group (SIG) and it represents a standard for wireless personal area networks (WPANs) [33]. Bluetooth is designed to be a very low power technology for peer-to-peer communications, and it operates in the 2.4-GHz ISM band. In comparison with WLAN, the gross bit rate is lower and the range is shorter (approximately 10 cm to 10 m [35,36]). The Bluetooth SIG groups include a local group that investigates the use of Bluetooth wireless technology for positioning. Bluetooth technology commonly uses proximity and RSS methods to estimate positions [36].

Dead Reckoning. In dead reckoning, an object can approximately determine its current position by knowing the past position and the velocity with which it moves. Dead reckoning is a navigation technology that needs to begin with a known position; and will then add and track changes. These changes can be in the form of Cartesian coordinates or velocity. With the right number of absolute position updates, dead reckoning's linearly growing position errors might be contained within pre-defined bounds [34]. In order to improve accuracy and reduce error, dead reckoning must use other methods to adjust the position of the object after each interval [44]. Pedestrian dead reckoning is an example that simply estimates the step length and direction of a walking person [34].

Image Based Technologies. Image based indoor positioning technologies, which are sometimes called optical methods, include camera and computer vision-based technologies [33,45]. Different types of camera can be used such as mobile phone cameras, omni-directional camera, and three-dimensional cameras; however, their performance varies due to the amount of information that can be extracted from their images [38]. The success of image-based technologies relies on different factors, such as; improvement and miniaturization of actuators, advancement in the technology of the detectors, an increase in the data transmission rates and computational capabilities and development of algorithms in image processing [45]. Image based positioning systems can be categorized into two main categories; ego motion systems which use a camera's motion relative to a rigid scene to estimate the current position of the camera and static sensor systems which locate moving objects in the images.

Pseudofiles. Since Satellites signals cannot penetrate most indoor environment such as buildings, coal mines, long tunnels and others, pseudofiles are used to generate GPS-like signals that can be used within indoor environments to allow GPS device to continue receiving signals from those transmitters rather than satellites. In order to cope with less accurate clock within pseudo lite transmitters which yields clock bias error, different techniques were developed. Pseudo lite-based indoor navigation may differ from system to another depending on the transmitting devices such as pseudofiles, synchronies, localities, and transceivers [46]. Wang have presented a survey of historical pseudolite developments including pseudo lite-base positioning and technical challenges [47]. Similarly, Eriksson and Badea studied different pseudolite-based indoor navigation systems and provided some recommendations. Pseudolites for indoor environments are still negatively affected by multipath, signal interference among pseudolites, weak time synchronization due to less accurate clocks within pseudolites, and carrier phase ambiguities [46]. Several pseudolites based positioning systems were developed recently that vary in their accuracy and coverage [48-51].

Indoor positioning applications may require different quality attributes Therefore, IPSs should be carefully chosen to meet the requirements of the application. Table 5 provides a comparison between indoor positioning technologies in terms of advantages and disadvantages of each technology that needs to be considered during the IPSs selection process.

Kok et al., designed an indoor positioning approach in 2015 based on a sensor fusion method that combines inertial sensors and time of arrival measurements from UWB. Their approach depends on an UWB transmitter that is rigidly attached to inertial measurements unit and a number of UWB receivers placed indoors. UWB measurements here are modeled using a heavy-tailed asymmetric distribution that handles the delays of measurements due to NLOS and multipath. In order to obtain information of a position from the UWB measurements, the receivers' positions must be known and their clocks must be synchronized. Their experiment shows that their UWB measurements model lead to accurate position estimates [52].

Positioning of human body movement for cluttered indoor environment uses wearable UWB technology to obtain 1–2 cm error using eight base stations, while four base stations were used in different shapes to obtain a slightly lower accuracy for locating body movement [53]. In most configurations, peak detection algorithm was used to estimate TOA of the received signals.

In 2013, Zaric et al., presented the ability of localization of a conformal wall-embedded tag in a suitcase using UWB. The system contains two main modules: an optical position measurement system that is based on a web-camera and an UWB positioning system. The author attempted to test the localization accuracy and the tag detection reliability in different situations of a suitcase. The test shows average positioning error of around 8 cm [54].

Generalized Gaussian mixtures (GGM) approximative method was compared and outperformed extended Kalman filter to provide more accurate position estimation in movement tracking in environment with uncertainty while still keeping computational complexity reasonable to use in mobile devices [55].

Krishnan et al., have used TDOA for UWB indoor positioning system where the site has been divided into cells and each cell has four UWB readers mounted on the top corners to have line-of-sight with user tag. In this manner, the readers will be able to receive the signals from the user tag then send the time of arrival to a central processing unit to determine TDOA and find user location [56]. Rowe et al., designed one dimensional system with two sensors and one tag using TDOA-based algorithm to determine the tag location [57]. On-off keying (OOK) modulation was used to overcome the collision induced by synchronous tag transmission, increase the performance, and decrease the cost and power at the same time. Leitinger et al., utilized prior knowledge of floor plan to improve positioning in multipath environment using the concept of equivalent Fisher information [58].

Cyganski et al., presented a new way to utilize multi-carrier signal to performance degradation due to multipath signals within indoor environment [59,60]. The authors applied matrix decomposition-based multi-carrier range recovery algorithm to improve accuracy of positioning in severe multipath environment.

In 2012, Ruiqing Ye presented a detailed study about UWB localization systems that have different accuracy requirements and complexity. He developed a three-dimensional localization system with a centimeter accuracy using UWB technology to track miniature mechanical parts in an airplane wheel. The system uses a TDOA algorithm and four receivers in order to track these parts. Two technical challenges are observed after testing the system in an environment that is rich with metal objects: angle-dependent waveform distortion and path overlap. He proposed a range estimation method to reduce the error caused by the path overlap. Also, the author discussed the effect of the receiver configuration on the performance of TDOA. Moreover, the author designed a wireless localization system that has a centimeter accuracy [61].

Zwirello et al., provided a complete demonstration of designing an UWB positioning system in 2012 that includes a choice of positioning method, access points' placement, error sources analysis, and simulation and verification of measurement. The authors also implemented and evaluated various TDOA algorithms. They concluded that a combination of modified Bancroft and Levenberg Marquardt algorithms are the most efficient algorithms. A series of evaluations and tests were conducted in designing the corresponding UWB positioning system. They improved the average accuracy from 9 to 2.5 cm [62].

Garcia et al., presented a robust UWB indoor positioning to operate in a highly complex indoor scenario in which NLOS condition is highly expected [63]. The system detects the NLOS condition using channel impulse response in order to effectively apply Extended Kalman Filter that improves the accuracy.

Chapter 3
Methodology

3.1 Technique Selection

This research uses the received signal strength indication (RSSI) from LoRa technology as a core method with enhanced analysis using artificial neural networks (ANN) to conduct the LoRa-based intelligent indoor localization system. Although there are many potential techniques and technologies, such as WiFi, Bluetooth, or other existing wireless technology, available to be deployed for localization application. The use of both multiple LoRa modules combining with ANN tool is not much realized and widely used for such an application. Due to the advantage of wide coverage of LoRa technology compared to other candidates and the flexibility to develop its own gateway device, it can be considered as a suitable approach for variety of size of localized area ranging from, for example, a small warehouse and even a large-size indoor factory. Furthermore, the ANN tool is also utilized in order to reduce the complexity to build their own proprietary function, which is in fact difficult to be replicated by other users, especially to advocate the rapid deployment and simple utilization in actual use case. In addition, some concerns of location error might need to be taken into consideration, which includes the occurred error signal strength that may cause by the interference from that surrounding environment and the insufficient performance of trained ANN model that may be affected by unreliable collection of intend data in some circumstances.

3.2 Experiment Process and Design

In this research, the experiment has deployed four sets of LoRa modules two meters above from the ground in order to spontaneously transmit the power signal to a mobile receiver moved manually along the area divided in grid table. The grid table of the area are both 5 meters long in an identical square with each 20 centimeters square for all sub-grids. The 20 centimeters displacement is the minimum distance of each time the mobile receiver needs to move to collect the RSSI data from all four of LoRa modules for further training in order to develop the corresponding model of ANN according to that localized area. In some other existing localization experiments related to the use of wireless modules for indicating the positioning coordinates, there are also cases where only two modules are enough to conduct the indoor localization, but the best practical approach is recommended to use at least three modules as a minimum requirement similar to the concept of global positioning system (GPS). However, this research uses four modules to increase the performance and accuracy of the obtained signal from the receiver for the correct analysis in ANN tool. Nevertheless, there are three major factors involved in this experiment displayed in Table 6, including signal intensity and surrounding environment.

Table 3.1 The Definition of Major Factors Initially Managed in this Reseawrch

No.	**Factor**	**Description**
1	Independent variable	intensity of the signal
2	Dependent variable	correctness of the signal intensity
3	Controlled variable	the controlled environment in experiment

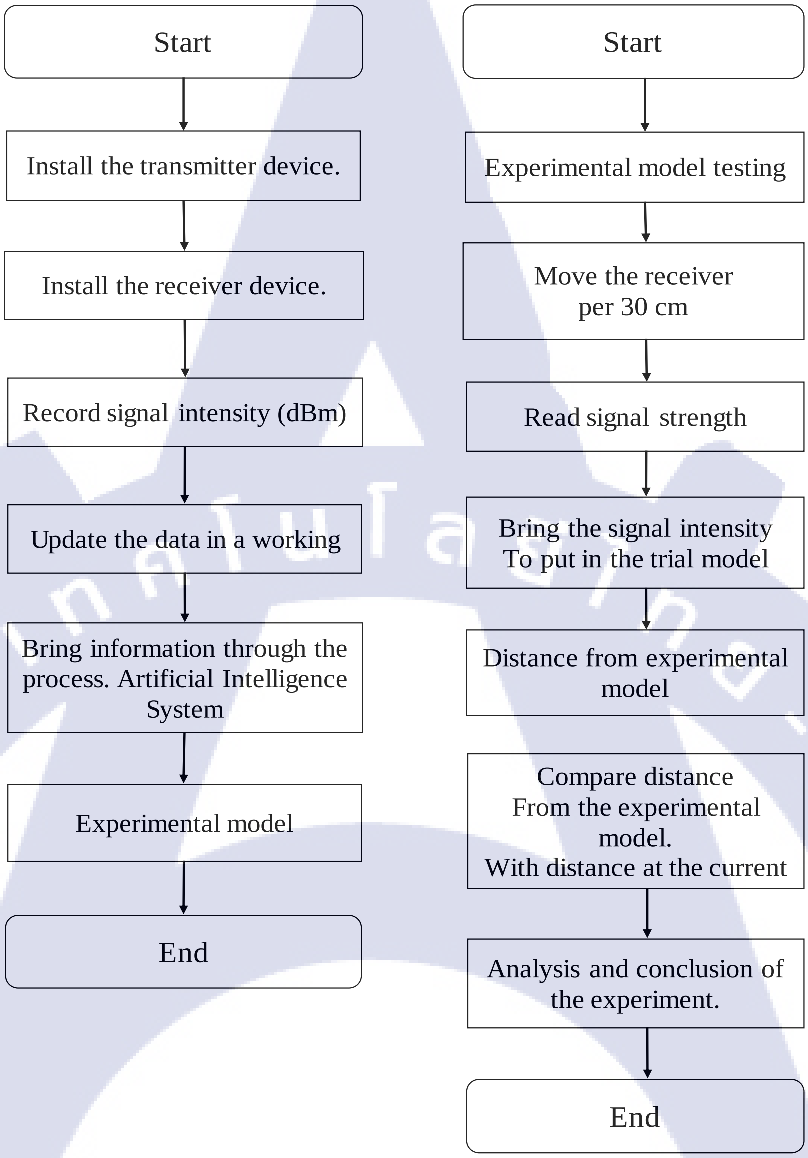


Figure 3.1 The overview flowchart shows the overall process of this research

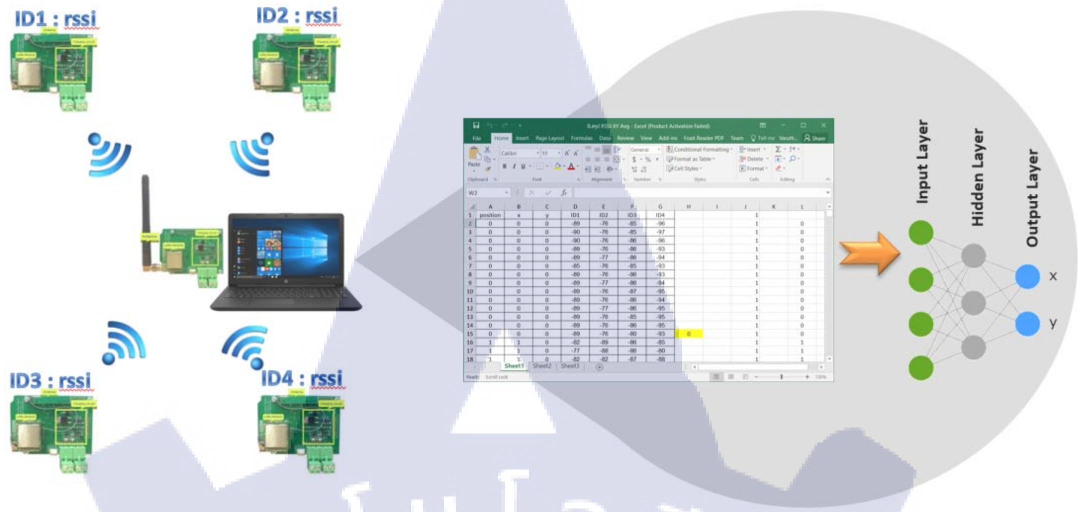
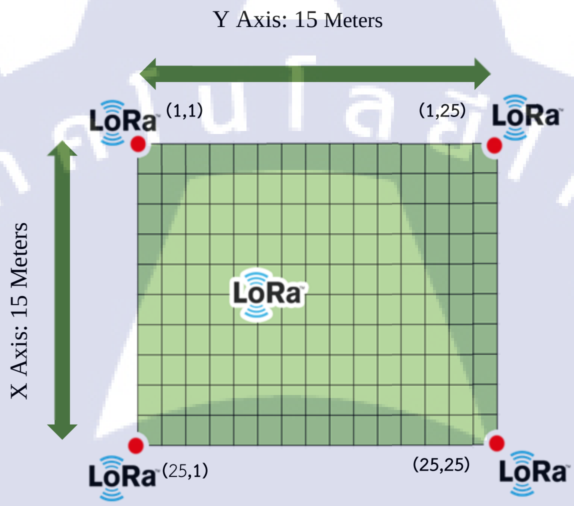


Figure 3.2 The diagram illustrating conceptual design of the intelligent indoor localization

The experiment process could be categorized as two major processes and their sub-processes shown on flow charts in Fig. 42. According to the proposed flow chart on the left-hand side, the first flow chart displays the sub-processes involve with the data collection as dataset for training and optimize the corresponding model of ANN. On the other hand, after obtaining the trained model, the ANN model has been tested and performed in actual prototype localization system. After completing the assembled system of wireless LoRa-based module for both transmitter and receiver and the controlled area prepared for experiment the intelligent indoor localization. In Fig. 43, the illustrated diagram has been depicted as to provide the overview of designed end-to-end system of the LoRa-based localization application. As shown in the figure, all four transmitters emit the signal in term of RSSI all the time from their stationed positions to the moving receiver dedicatedly for recording the varied data from each corresponding coordinate along the grid table of the floor. The received data has been recorded in CSV file within the excel software, and then the MATLAB toolbox import those data into its program for training the ANN function associating with those contexts. The aforementioned process is, in fact, done in the portable PC laptop connecting to LoRa-based receiver through serial communication with USB port. After all the pre-configuration and ANN training have all been accomplished, the conducted system will then be operated again in the prototype situation of the same controlled area in order to obtain the result, and that result will be further verified its performance and correctness afterwards.

3.3 Modeling, Data Collection, and Simulation

Refer to the modeling of ANN, the research uses MATLAB with ANN toolbox for creating the ANN model and perform the simulation within the program.



As depicted in Fig. 44, the grid.

Figure 3.3 The graphical localized area depicts divided grid with association with LoRa modules

Table 3.2 The Validation and Test Data of Neural Fitting of Ann

Process	**Percentage of Usage**	**Quantity of Samples**
Training	80%	502 samples
Validation	10%	62 samples
Testing	10%	62 samples

area has been divided into 25 steps – every 20 centimeters of the whole 5 meters – for both side of X-axis and Y-axis. In short, the receiver needs to move for about 225 steps in order to gain the total RSSI samples of each coordinates within the localized field. Then the data corresponding to each coordinate are imported in to the ANN toolbox in MATLAB in order to train the model to work well with the situation. In this case, this research deployed 80% of the total samples for training, 10% for validation, and the other 10% for testing as indicated in the table 7.

The Fig.3.4 displays the scenario where the inputs including relating RSSI and its coordinates to the neural network training tool, which comprises of Simulink and block parameter to adjust and configure the ANN model. The inputs are included of four sets of RSSI data and two additional axises of X and Y. For the architecture model of ANN, the model is practically the two-layer feedforward neural network with Levenberg-Marquardt algorithm.

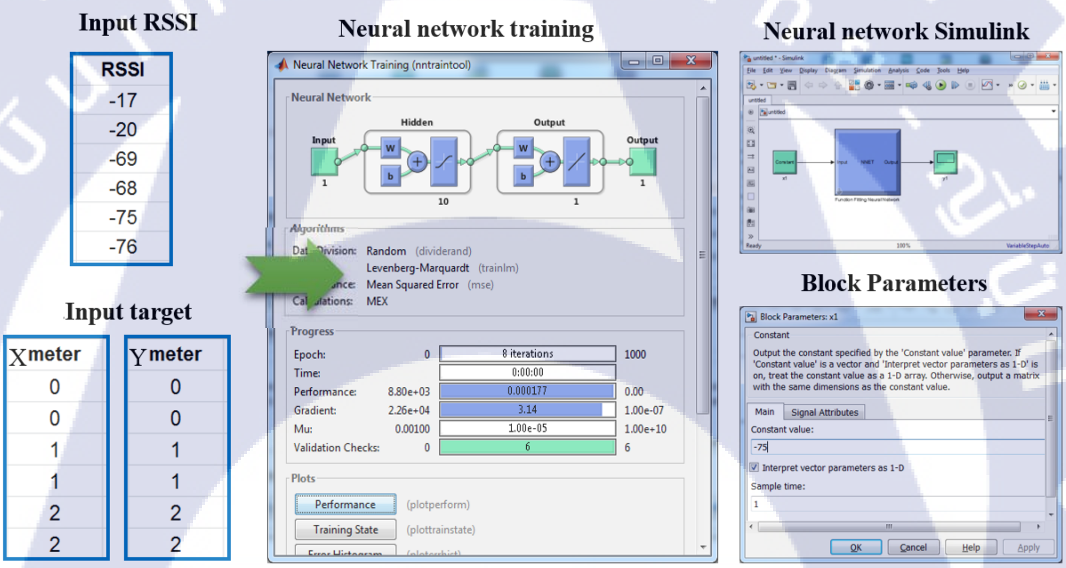


Figure 3.4 The example of ANN tool performed in MATLAB platform

3.4 Model Validation and Test

The research mainly focuses on testing the system performance through ANN simulation rather than implementation with actual mobile receiver in order to validate the accuracy of the system again. Straightforwardly, the validation and test are inspected using the ANN model as mentioned previously from the prior topic that only 20% of the total samples are used to validate and test the reliability of the system in terms of both performance and accuracy.

3.5 Main Tools used within the Experiment

Hardware List

3.5.1 LoRa-based transmitter module – 4 sets

The overall modules of the senders are identical in configuration and are essentially used as fixed at each position of the coverage area transmitters to emit the RSSI to the targeted receiver that move around the field.

3.5.2 LoRa-based receiver module – 1 set

The receiver designed to move around the coverage area of localization system as for receiving the RSSI data from all transmitters at each coordinate of the grid. The receiver is manually moved along the entire area to gain the information.

3.5.3 Portable PC laptop – 1 set

The PC laptop is to manage the system and collect the received data while performing and testing the experiment. Moreover, all the records are kept in form of CSV file and used to train the ANN model within the software here as well.

Software List

3.5.4 Arduino IDE software

Arduino IDE software is for programming the script to communicate with both the LoRa-based transmitters and the sole receiver.

3.5.5 Math work MATLAB software

The ANN toolbox from MATLAB has been utilized to model the feedforward neural network from training data gathering by the PC laptop. The parameter of the ANN model can be configured, and the training process is also performed here on ward.

Chapter 4
Result and Discussion

4.1 End Device Design

A. Circuit and System Designs

The proposed LoRa module has been designed as a stand-alone device, which can be equipped with another microcontroller. Fig.46 shows the block diagram of the proposed LoRa End-Node. It can be seen from Fig.46 that the end-node comprises a LoRa Module with built-in an antenna. This LoRa module is connected to the Arduino Pro-Mini that processes all signals both inputs and outputs. The power supply system is a Lithium-Ion Batter (3.7V) that is connected to a battery charger module TP4056. The TP4056 module become the power supply in order to step-down the 3.3V voltage regulate module.

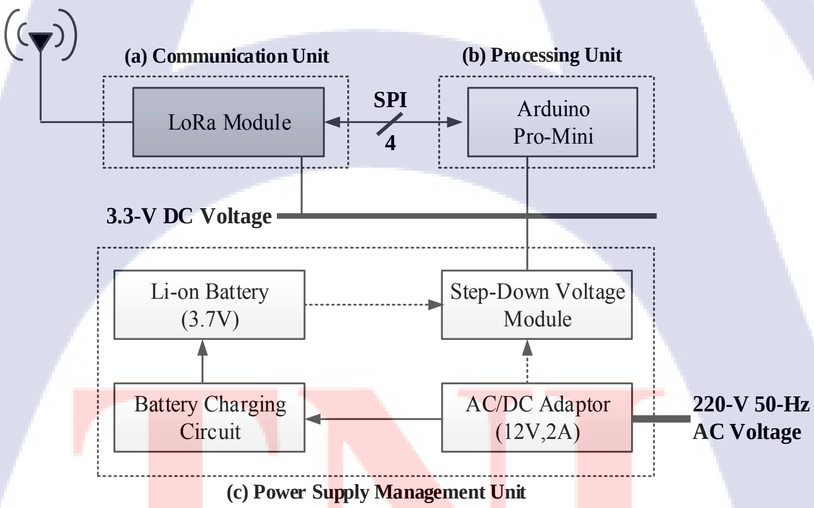


Figure 4.1 Block diagram of LoRa module equipped with Arduino Pro-Mini, and Regulator, and a built-in

Table 4.1 Technical Specification of Circuit Modules

Circuit Modules	Specifications
LoRa Chip	168 dB maximum link budget +20 dBm - 100 mW constant
SX1276/77/78	RF output vs. Supply +14 dBm high efficiency PA Programmable bit rate up to 300 kbps High sensitivity: down to -148 dBm Bullet-proof front end: IIP3 = -11 dBm Excellent blocking immunity Low RX current of 9.9 mA FSK, GFSK, MSK, GMSK, LoRaTM and OOK 127 dB Dynamic Range RSSI
Antenna ANT-RA57-915	890-915MHz, Center Frequency at 915 MHz 2-dBi Gain VSWR ≤ 2 Vertical Polarization 50-Ω Impedance
Arduino Pro-Mini MEGA328P	Operating Voltage at 3.3V or 5V 14 Digital I/O Pins and 6 Analog Input Pins Flash Memory of 32kB SRAM of 2 kB EEPROM of 1 kB

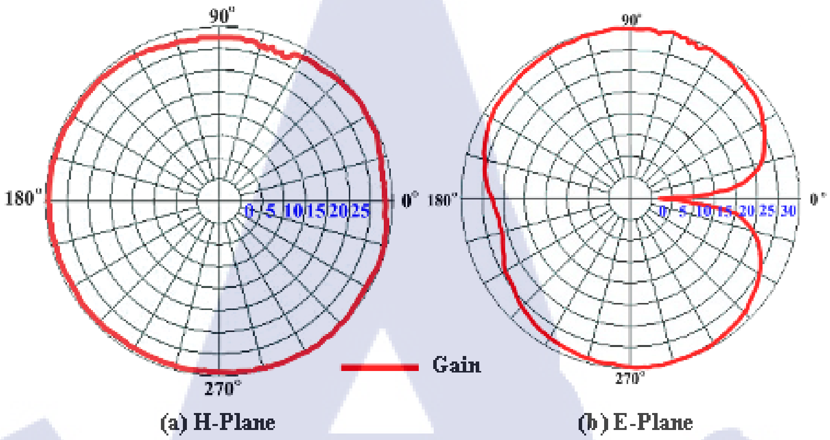


Figure 4.2 The radiation pattern of an antenna; (a) H-Plane, (b) E-Plane

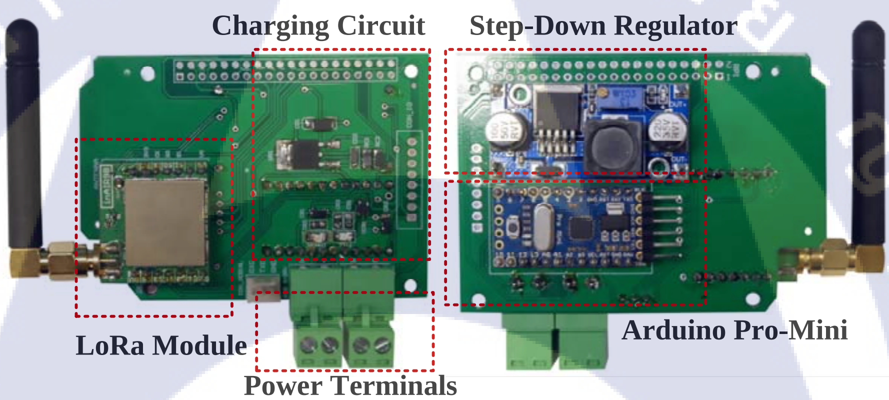


Figure 4.3 The assembled two-layer circuit prototype of the LoRa-based communication module with built-in monopole antenna

Table 4.1 summarizes technical specifications of circuit modules. The LoRa is apparently not only offers high efficiency of +14 dBm but also minimizing current consumption of 9.9 mA. In particular, the LoRa module provides high dynamic range RSSI of 127 dB with whilst excellent blocking immunity, which is suitable for indoor localization. It is also seen in Table 8 that the antenna is a typical for LoRa communication at a center frequency of 915 MHz and the gain is 2-dBi with a maximum Voltage Standing Wave Ratio (VSWR) of two. In accordance to the antenna, Fig. 47 depicts the radiation pattern of an antenna both in H-plane and E-plane. As the polarization is vertical, the directivity in H-plane provides a full gain of approximately 40 dBi in all direction whilst the gain drops to zero for E-plane at 0O. The experiment shall be carefully considering a vertical polarization in order to receive a RSS properly. Finally, Table 8 also indicates that the Arduino Pro-Mini MEGA328P was chosen as a processing unit with 14 digital I/O pins and 6 analog input pins and sufficient memory for application in indoor localization, i.e. Flash Memory of 32kB, SRAM of 2 kB, and EEPROM of 1 kB. Fig. 48 illustrates the assembled two-layer circuit prototype of the LoRa-based communication module with built-in monopole antenna. As for experiment on indoor localization 5 boards were assembled, four of which will be employed as APs and one for RP.

4.2 Indoor Measurements

Evaluations of Reliability of LoRa Communications

Preliminary evaluation of the LoRa communication module was conducted at Thai-Nichi Institute of Technology where the gateway was installed at the 6th floor of C-building with a height of 550 meters. Fig. 49 shows a physical map for testing signal strength with an increment of 100 meters. The performances were investigated by RSSI, which is usually expressed in dBm from 0 to approximately lowest at -120 dBm. In addition, Signal-to-Noise Ratio (SNR) defined as the ratio of signal power to the noise power has also been investigated. Fig. 50 shows plots of measured RSSI in dBm and SNR in dB versus a distance. The RSSI decreased from 0 to around -90 dBm within the first100 meters. From the distance of 100 meters to 500 meters, the values of RSS decreased from -90 dBm to approximately -100 dBm before signal lost. Meanwhile, the SNR is positive till the distance of around 160 meters and the SNR was then decreases to -18 dB at 500 meters. Such results indicate that the LoRa communication is reliable with satisfied SNR values for further implementations. As mentioned earlier, the width and length of a floor are 15m. and 15m., respectively. Therefore, the overall performance is sufficient for indoor localization implementation.

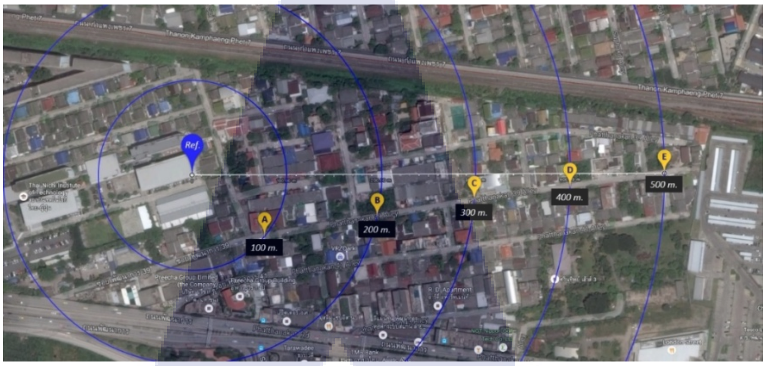


Figure 4.4 Test for signal strength coverage area at C-Building of Thai-Nichi Institute of Technology

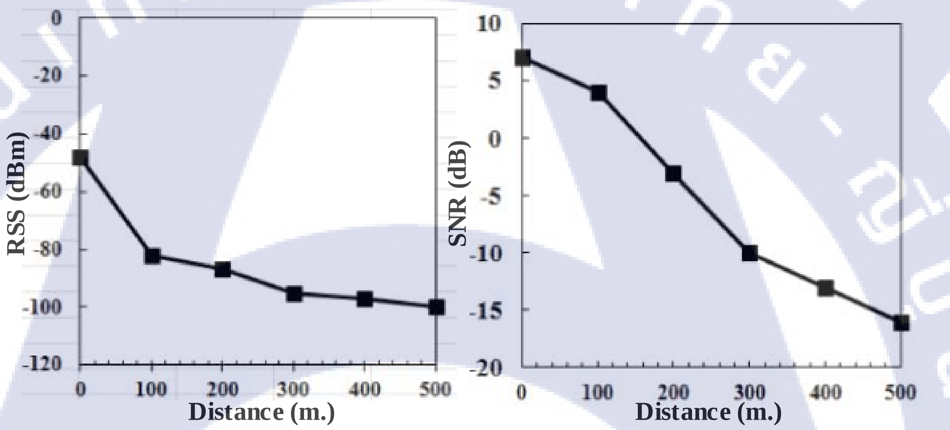


Figure 4.5 Plots of RSS versus a distance for one-to-one communication tests

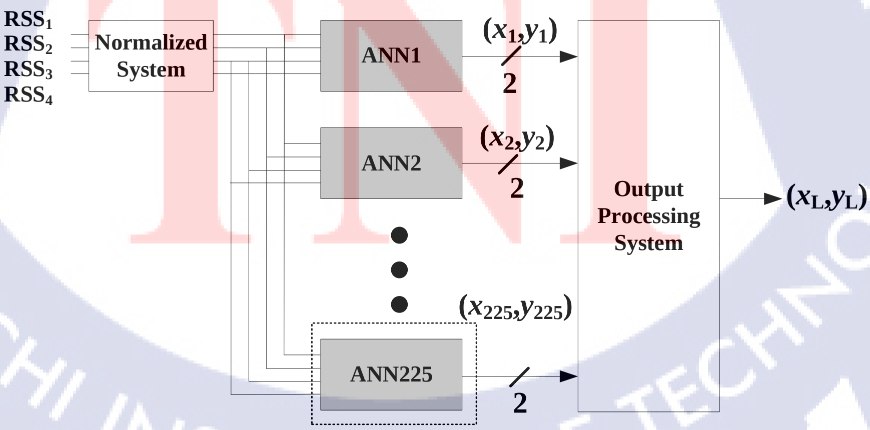


Figure 4.6 ANN-Based Indoor Localization with output processing system

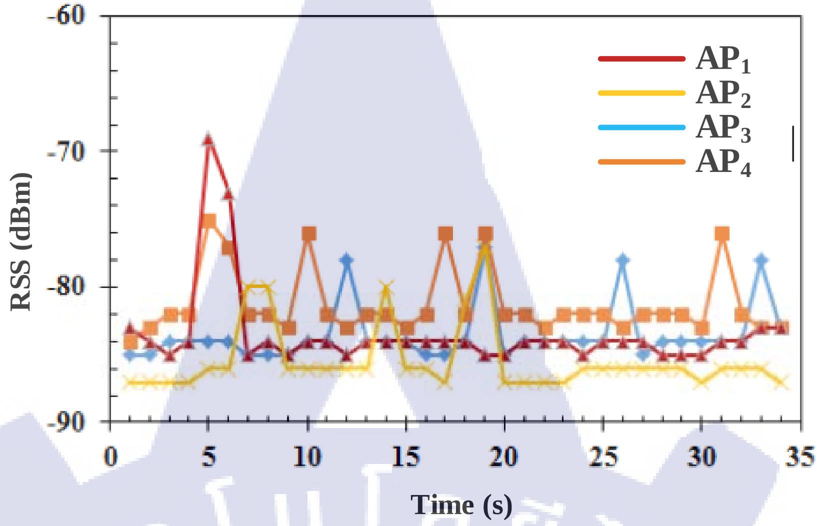


Figure 4.7 Examples of a received RSS in dBm of the four APs in time-domain

4.3 Simulation Results

Experimental Results for Indoor Localizations

The proposed indoor localization system has been conducted based on the system model depicted in Fig.55. First, a one-to-one communication using two LoRa modules was investigated in terms of RSS for evaluating a characteristic curve of RSS values versus a distance as shown in Fig. 50. The plots reveal that the values of RSS decrease from -40dBm to approximately -120dBm over an entire distance range of 15 meters. The characteristics is relatively linear with sufficient different in RSS values, and therefore it can be concluded that the utilization of RSS from LoRa technology is applicable for indoor localization within 15 meters.

Second, each of location in the coverage area was recorded as a fingerprint database, and it was trained by ANN. Fig. 51 shows ANN-Based Indoor Localization with output processing system.

The system comprises 255 modules of trained ANN in order to distinguish each location where the output system determines the location. The ANN is a back propagation and each block was trained with customized number of hidden nodes with a golden error of less than 10-3. Activation functions of a hidden layer is a sigmoidal function while the output function is a piecewise-linear function, i.e. f(x) =

0 for x<0, f(x) = 0 for 0<x<1 and f(x) = 1 for x>1. The output activation function assists a precise location on the area of experiments.

Third, Fig. 1.8 depicts Examples of a received RSS in dBm of the four APs in time-domain at a particular location. It can be seen in Fig. 52 that the RSS are relative different. As a result, Fig. 53 illustrates correct and wrong indoor localization over 15 m2. There are 11 locations that the proposed system cannot be localized and there in a middle of an area. This is because of close values of RSS received from the four APs. Therefore, the error is 4.88%, yielding the accuracy of 95.22%.

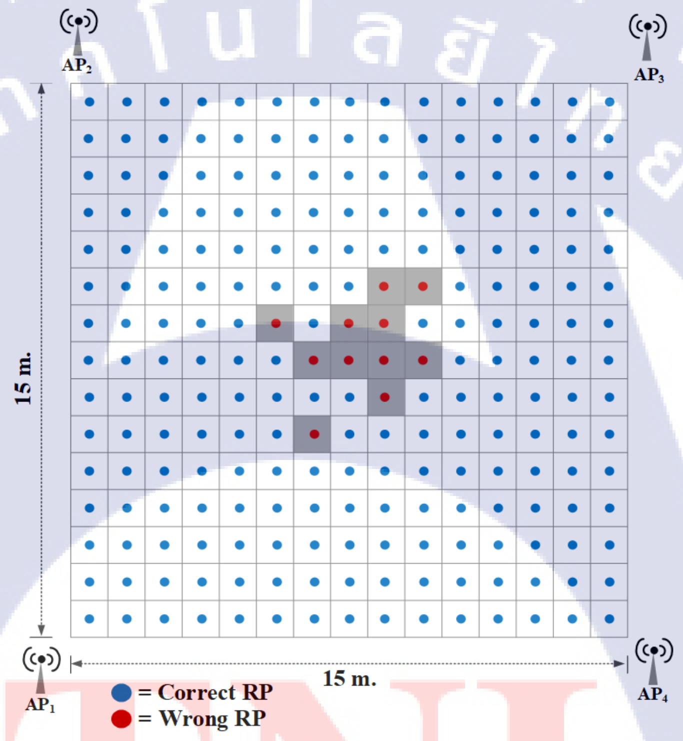


Figure 4.8 Results of correct and wrong indoor localization over 15 m^2

4.4 Positioning Algorithm

In RSS-based algorithms, the tracked target measures the signal strength for received signals from multiple transmitters in order to use signal strength as an estimator of the distance between the transmitters and receivers. This way, the receiver will be able to estimate its position relative to the transmitter nodes. Although RSS is sensitive to multipath interference and a small-scale channel effect that causes a random deviation from mean received signal strength, it is used frequently with unrealistic assumptions. For example, the transmitted power and path loss exponent are already known, and the transmitter antennas are isotropic [64,65]. According to Pittet et al., the accuracy of RSS for non-line-of-sight (NLOS) and multipath environment is low, which shows clearly that RSS is not the right estimation method for indoor positioning systems [66]. Gigl et al., explored the performance of RSS algorithms for positioning using UWB technology [67]. They also studied the effect of small-scale fading on the system accuracy; however, a simulator based on the UWB channel model 802.15.4a was used to evaluate the algorithms rather than relying on real scenarios for indoor environments. Leininger et al., used maximum likelihood estimator as well as floor plan information to improve positioning in the existence of diffuse multi path for the NLOS environment [68].

This thesis therefore studies an indoor localization technique through the utilization of Received Signal Strength Indicator (RSSI) of LoRa Technology. The methodology employs five sets of LoRa nodes and four of which were utilized as statistic nodes, radiating a signal power from 2-meter high from the floor. The receiving node is placed in a particular coordinate on the floor. The RSSI values were employed as inputs for Artificial Neural Network (ANN) for estimation of the coordinate of the receiving node. The LoRa frequency is 915 MHz and the microcontroller are Arduino Pro-Mini that processes all signals with Lithium-Ion Battery.

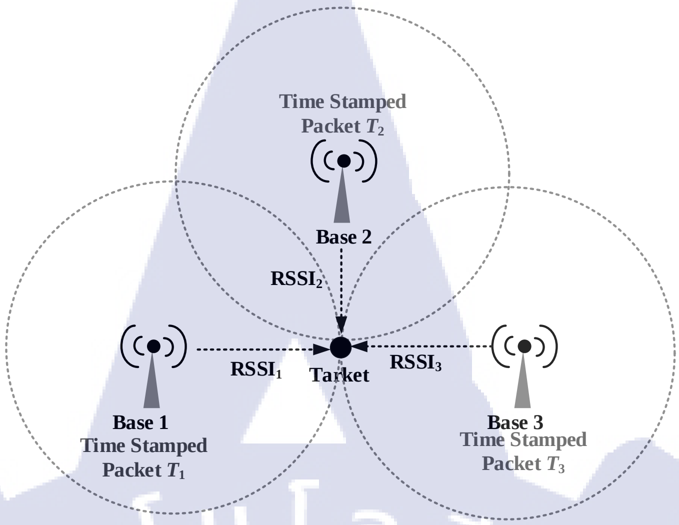


Figure 4.9 A generic visualization of indoor positioning techniques with three base stations, demonstrating both RSSI and time stamped packets

4.5 Reviews on Typical Indoor Localization Approaches

Several wireless technologies have been realized for indoor localization approaches, depending on performances and also limitation of mathematical models for location estimation. Typically, major performance metrics associated with localization systems involve the following areas, i.e. (i) an accuracy that can be described as an error distance between estimated and actual locations, (ii) The responsiveness that determines speed of updating time of estimated location, (iii) coverage that determined the network coverage under a designated area of localization, (iv) adaptiveness which refers to an ability of the localization system to cope with environmental influence changes that affect to overall system performances, (v) Scalability in which a localization system can potentially operates with a larger number of location requests and a larger coverage, and (iv) cost and complexity, which are on of practical concerns, involving extra infrastructure, additional bandwidth, money, lifetime, weight, energy, and nature of deployed technology. Based upon the above-mentioned performances and suitability of localizing environments, this paper particularly summarizes indoor localization approaches with two categories, i.e. proximity and triangulation [69-70].

4.6 Proximity Detection Approach

Proximity detection is the simplest positioning method for implementing localization of a target. This method provides relative position between a target and a cell of origin, such as GSM, RFID, or Bluetooth, with known position and limited range. Typically, this method detects the target via the nearest position where the strongest signal is received. In recent years, this method has been deployed using beacon with short-range communications. However, the proximity-based method has a high variance which may not satisfy the need for localization.

4.7 Triangulation

Triangulation utilizes geometric properties of triangles to determine the target location, which typically has two derivations, i.e. angulation and lateration. On the one hand, angulation method refers to as Angle-of-arrival (AoA) method which determines the angle of arrival of the signal receiving from a known location at which it is received at multiple base stations. Geometric relationships can subsequently be utilized in order to estimate the location of the intersection of line angles. Although the angle of signal can be retrieved straightforwardly through directional antenna technology, the angle of stations may not exactly be the angle of received single due to the existence of multi-path and environmental reflections.

On the other hand, lateration method refers to a position determined from distance measurements obtained from multiple reference points. Fig. 54 demonstrates a generic visualization of indoor positioning techniques with three base stations, demonstrating both time stamped packets and RSSI. It can be considered from Fig. 54 that lateration methods can be classified into two types, including (i) time-based triangulation, and (ii) RSSI-based triangulation. General techniques for time-based triangulation are generally Time-of-Arrival (ToA) which directly measures time stamped packet transmitted from base stations or versa vice. Meanwhile, Time Difference of Arrival (TDoA) is a measure between multiple pairs of reference points with known locations and exploits relative time measurements at each receiving node in place of absolute time measurements. Besides, Received Signal Strength (RSS) as also shown in Fig. 54 has been used to represent received signal property. The distance can be obtained and the location can be calculated based on by receive signal strength property.

4.8 Received Signal Strength

Received Signal Strength Indication (RSSI) typically refers to as a measurement of the power existent in a received radio signal. The RSSI values are generally measured in dBm and have typical negative values ranging from 0 to approximately -120 dBm, which is a noise floor. As wireless Radio Frequency (RF) signals traverse air, a number of effects, such as noises and air resistance, directly affect signal degradation, resulting in attenuation of a received power. Based upon the standard definitions of terms for antennas, i.e. IEEE Standard 145-1993, the Free-Space Path Loss (FSPL) can be modeled as

$$P_{\mathrm{R}} = P_{\mathrm{T}}\left(\frac{\sqrt{G_{\mathrm{R}}}\,G_{\mathrm{T}}\lambda}{4\pi d}\right)^2 \tag{4.1}$$

where PR is a received power, PT is a transmitted power, GR is a transmitting antenna gain, GR is a receiving antenna gain, λ is a signal wavelength, and d is the distance between the two antennas. Eq. (4.1) can also be described in Decibel (dB) as follows.

$$P_{\mathrm{R}}[\mathrm{dBm}] = P_{\mathrm{T}}[\mathrm{dBm}] - 20\log_{10}(d) - 20\log_{10}\left(\frac{4\pi}{\lambda}\right) \tag{4.2}$$

It should be noted that real model of (4.2) should involve a signal loss caused by shadowing effect, which is a result of fluctuations in measurements due to various disturbances such as interference from transmissions, weather effects or scattering. This paper therefore proposes the RSSI-based triangulation through the use of fingerprint database technique for indoor localization.

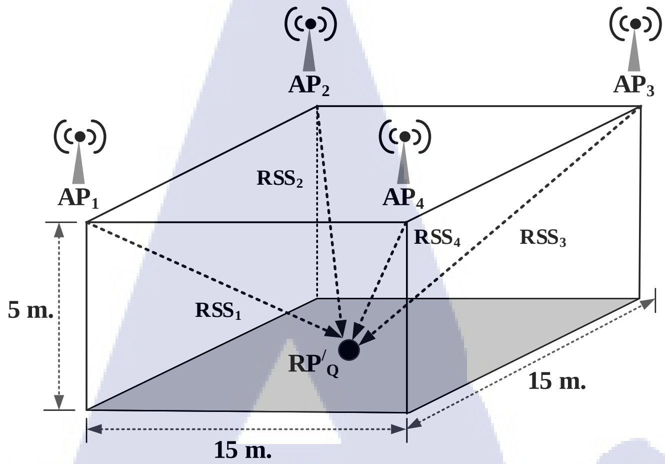


Figure 4.10 System model geometry and area coverage, involving four APs and a single target in a reference point RP/Q

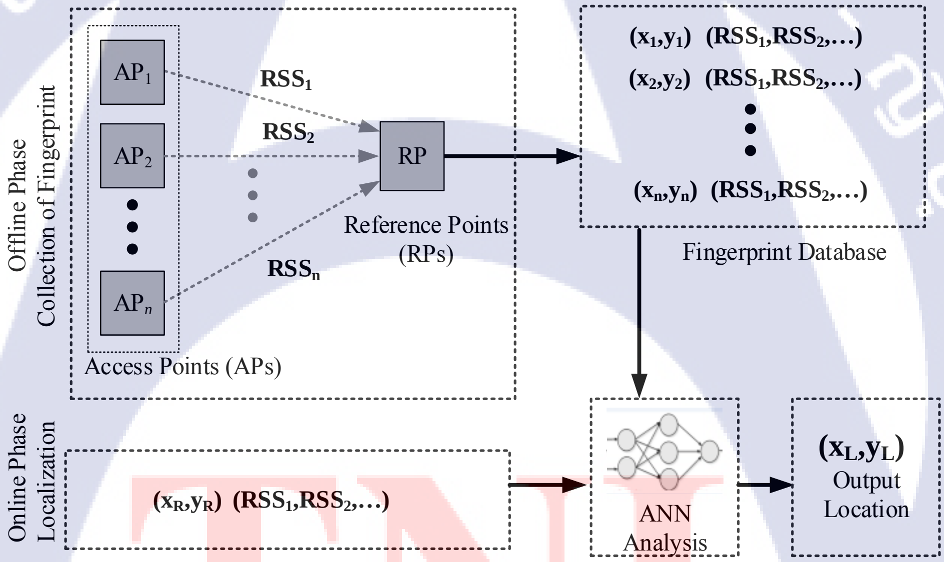


Figure 4.11 The overall architecture of the proposed RSSI-based indoor localization using LoRa technology with fingerprinting database

4.9 Proposed Rssi-Based Indoor Localization Using Lora Technology with Fingerprint Database

Fig. 4.11 depicts system model geometry and area coverage, involving four APs and a single target in a reference point RP/Q. The designed system employs four Access Points (APs) which are all LoRa transmitters. A single receiving module RP/Q is also a LoRa receiver located at a particular Reference Points (RPs). The width and length of a floor are 15m. and 15m., respectively, and hence the area is 225 m2. The height of those four APs is 2m. The coordinate (x, y) is 1m2. Fig.56 shows the overall architecture of the proposed RSSI-based indoor localization using LoRa technology with fingerprinting database. It can be considered from Fig.56 that location fingerprinting comprises off-line and the on-line phases. The off-line phase constructs a map for the targeted area, and coordinates of RPs are designated. Subsequently, RSS values received from each RP from all APs are collected and stored in a fingerprint database. In the on-line positioning phase, the unknown position of a target is estimated Artificial Neural Network (ANN) which has been trained by a fingerprint database. In this paper, RSS probability distributions of all APs at all RPs are required to be stored for training ANN. The fingerprint of the ith RPs can be defined as follows.

$$R_i = \begin{bmatrix} P(A_1T_1|L_i) & P(A_2T_1|L_i) & \cdots & P(A_NT_1|L_i) \\ P(A_1T_2|L_i) & P(A_2T_2|L_i) & \cdots & P(A_NT_2|L_i) \\ \vdots & \vdots & \vdots & \vdots \\ P(A_1T_M|L_i) & P(A_2T_M|L_i) & \cdots & P(A_NT_M|L_i) \end{bmatrix} \tag{4.3}$$

where An, n=1⋯N, is the nth of AP, T is the measurement of RSS, Li is ith RP, and P can be expressed as follows.

$$P(A_1T_M|L_i) = \frac{C_{T_m}}{N_i} \tag{4.4}$$

where Ni is the total number of training samples collected at the ith RP, and CTm is the number of Tm appearing in the training data at the ith RP. Consequently, the fingerprint database D is given by

$$D = [R_1, R_2, \cdots, R_w] \tag{4.5}$$

where w is the total number of RPs in the coverage area. In addition to fingerprinting database, this work alternatively employs ANN instead of other common techniques such as database matching or search algorithm. The supervised learning ANN with Back-Propagation Learning Algorithm was chosen for training the database D. Fig. 4 shows the structure of a realized ANN for determining the location of an output coordinate (x, y). It is apparent in Fig.4 that the four inputs are RSS1 to RSS4, which are normalized to be in a region of (0, -1) dBm. The optimized hidden layer comprises 30 nodes and the two output nodes provide the coordinate (x, y).

Chapter 5
Conclusion

5.1 Conclusion

Low–Power, Wide-Area Networks (LPWAN) are projected to support a major portion of the billions of devices forecasted for the Internet of Things (IoT). LoRaWAN™ is designed from the bottom up to optimize LPWANs for battery lifetime, capacity, range, and cost. A summary of the LoRaWAN™ specification for the different regions will be given as well as high level comparison of the different technologies competing in the LPWAN space. Indoor Positioning Systems uses sensors and communication technologies to locate objects in indoor environments. IPS are attracting scientific and enterprise interest because there is a big market opportunity for applying these technologies. There have been various previous surveys on indoor positioning systems. However, most of them lack a solid classification scheme that would structurally map a wide field such as IPS, or omit several key technologies or have a limited perspective; finally, surveys rapidly become obsolete in an area as dynamic as IPS. The goal of this thesis is to provide a technological perspective of indoor positioning systems, comprising a LoRa® technology classify the existing approaches in a structure in order to guide the review and discussion of the different approaches.

Based on real-world application, a positioning device like GPS cannot be manipulated indoor, because signals between GPS receivers and satellites are blocked by building walls. Several indoor positioning approaches, therefore, are designed to eliminate such problem. The researcher realizes a key problem of AGV cars in order that when AGV cars are ordered for purchase, a magnetic stripe reader must be installed in the cars as a driving navigator. The cars move on right directions up to the magnetic stripe reader that detects directions or routes from the magnetic stripe installed on the plant floor. The problem found is that after the magnetic stripe is used for a period of time, it will wear out. As a consequence, there are frequent purchase orders for the new ones. Prior to a new one to be installed, the old one must be removed. Therefore, this is not only about too frequent replacement of the magnetic stripe but also the waste of time and installation payment every time when such problem occurs. It leads to the discontinuity of manufacturing processes in industrial plants as it has to wait until the installation or the replacement is finished. This problem inspired the researcher to invent and develop an indoor wireless positioning system as solution of the traditional navigation system of AGV cars.

As a result, this thesis has introduced an indoor localization technique through the use of Received Signal Strength Indicator (RSSI) of LoRa Technology. The LoRa chip from SEMTECH has been implemented on a compact board with built-in antenna. The Arduino microcontroller was employed as a core processor with a step-down switching regulator. Five sets of LoRa nodes were implemented and four of which were utilized as statistic nodes, radiating a signal power from 5-meter high from the floor. The localization has exploited 255 modules of trained ANN in order to distinguish each location. The resulting error the error is 4.88%, yielding the accuracy of 95.22%. The result provides satisfactory accuracy and low-power operation as for an alternative.

5.2 Suggestions and Recommendations

During the experimental process of this research, found that the Received Signal Strength is changed which might be coming from the voltage drop. After checking this root cause, there is occurred from the small battery that used to provide the energy. As a result, the recording of the signal strength decreases and the transmission device stops working. Thus, the antenna should be turned into the experimental area and consider the appropriate energy providing to eliminating this problem.

5.3 Future works

The next propose for this research methodology has applied for indoor localization system especially for AGV cars because it is useful for, i.e. Facility Management, Street Lighting, Factories, Industrial Applications, Healthcare Applications, Airport Services Management, Smart Parking, and Smart Farm.

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Appendixes

A. Attachment Code

1. LoRa Receiver

```
#include <SPI.h>
#include <LoRa.h>
String inputString = "";
void setup() {
Serial.begin(9600);
while (!Serial);
Serial.println("LoRa Receiver");
Serial.println("CLEARDATA");
Serial.println("LABEL,Time,Count,RSSI");
if (!LoRa.begin(915E6))
{
Serial.println("Starting LoRa failed!");
while (1);
}
}
void loop()
{

int packetSize = LoRa.parsePacket();
if (packetSize)
{
while (LoRa.available())
{
char reads  = (char)LoRa.read();
inputString += reads;
}
Serial.print("DATA,TIME,");
int rssi = LoRa.packetRssi();
Serial.print(inputString); Serial.print(rssi);  Serial.println(",");
inputString = "";
```

```
}
}
```

2. LoRa Sender Node 1

```
#include <SPI.h>
#include <LoRa.h>
int counter = 0;
String id = "1,";
void setup() {
Serial.begin(9600);
while (!Serial);
Serial.println("LoRa Sender");
if (!LoRa.begin(915E6)) {
Serial.println("Starting LoRa failed!");
while (1);
}
}
void loop() {
Serial.print("Sending packet: ");  Serial.println(id);

LoRa.beginPacket();
LoRa.print(id);
LoRa.endPacket();
delay(656);
}
```

3. LoRa Sender Node 2

```
#include <SPI.h>
#include <LoRa.h>
int counter = 0;
String id = "2,";
void setup() {
Serial.begin(9600);
while (!Serial);
```

```
Serial.println("LoRa Sender");
if (!LoRa.begin(915E6)) {
Serial.println("Starting LoRa failed!");
while (1);
}
}
void loop() {
Serial.print("Sending packet: ");  Serial.println(id);
LoRa.beginPacket();
LoRa.print(id);
LoRa.endPacket();
delay(656);
}
void loop() {
Serial.print("Sending packet: ");  Serial.println(id);
LoRa.beginPacket();
LoRa.print(id);
LoRa.endPacket();
delay(656);
}
```

B. Academic Work

Intelligent RF-Based Indoor Localization through RSSI of LoRa Communication Technology. 2018 7th International Conference on Industrial Technology and Management

2018 7th International Conference on Industrial Technology and Management

Intelligent RF-Based Indoor Localization through RSSI of LoRa Communication Technology

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***Abstract*—Requirements on high-quality indoor localization approaches and the increase in ubiquitous computing and context-dependent have led to an emphasis on a continuous search for promising localization technologies and techniques. Typical RF-Based localization technologies such as Cellular, RFID, Bluetooth, Wi-Fi, Zigbee, and UWB have been widespread studied over the past decades. Recently, LoRa communication technology has suggested as a potential alternative to those of exiting wireless communication standards with low power consumption and low implementation costs. This paper therefore presents an indoor localization technique through the use of Received Signal Strength Indicator (RSSI) of LoRa Technology. The LoRa chip from SEMTECH was implemented on a compact board with built-in antenna. The Arduino microcontroller was employed as a core processor with a step-down switching regulator. Five sets of LoRa nodes were implemented and four of which were utilized as statistic nodes, radiating a signal power from 5-meter high from the floor. The receiving node is placed in a particular coordinate on the floor. The RSS values were employed as inputs for Artificial Neural Network (ANN) for estimation of the coordinate of the receiving node. The accuracy was approximately 95%. The result provides satisfactory accuracy with cost-effective and low-power operation as for an alternative for large scales deployments of indoor localization.**

Keywords*— *Indoor Localization; LoRa Technology; Received Signal Strength Indicator; Artificial Neural Network.

I. INTRODUCTION

An "Indoor Positioning System: IPS" generally provides a position or location of people or required objects in a closed physical space continuously and in real-time. Particularly, indoor positioning is emphasized in the fact that that the object has been moved from place to place.

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"Localization", however, emphasizes the fact that positioning is conducted in an ad-hoc and cooperative manner, and highlights that the application requires topological correctness of sensor locations whilst the absolute coordinate position is of minor importance. Localization is generally associated with rough estimation of location for optimal accuracy systems.

Unlike an "Outdoor Positioning System: OPS" in which the Global Positioning System (GPS) can suitably be utilized efficiently, the research area in indoor localization has continuously been of much interest through both existing and emerging communication technologies due to the need for various applications such as location based services in indoor environments, medical care, environmental monitoring,

guiding of the vulnerable people, or augmented reality. As a consequence of such applications, design and development of efficient indoor localization should consider some essential quality metrics involving, for instance, (i) accuracy and precision, (ii) coverage and resolution, (iii) latency in making location updates, (iv) infrastructure impacts, and (v) effects of random errors caused by signal interference and reflections.

Over the past decades, numerous approaches for IPSs have been proposed based on a variety of RF-based communication technologies such as Cellular (GSM/GPRS) [1], RFID [2], Bluetooth [3], Wi-Fi [4], Zigbee [5], UWB [6] and LoRaWAN [7]. Table 1 summarizes technological specification of communication technologies for IPSs. It can be considered in Table 1 that the cellular-based indoor localization relies on the mobile cellular network, remarkably the wireless telephone technology Global System Mobile (GSM) communication. Such cellular-based system generally estimates mobile user position in building with low accuracy, but power consumption is relatively high and the signal strength is based on a cell site under the main infrastructure. Consequently, indoor localization based on cellular network has received less attention than those of non-cellular based systems.

It is also seen in Table 1 that the Radio Frequency Identification (FID), which operates at a frequency 13.6 MHz, has been recognized as one of a potential technology for locating objects or people. RFID typically enables a one-way communication via noncontact and advanced automatic identification through radio signals. RFID consumes low power, and has widely been utilized a wide range of applications such as automobile assembly industry, warehouse management, supply chain network. However, RFID provides low data transfer rate and operates in a short range lower than one meter, a number of RFID tags is required and a complicated networks is ultimately required to be designed properly. Alternatively, Bluetooth, Wi-Fi, and ZigBee technologies that operate at 2.4 GHz with different protocols have also been utilized for indoor localization.

Bluetooth offers information exchange between devices with high security, low cost, low power, and small size. However, device discovery procedure is reiterated in each location finding, resulting in the increase in localization latency and power consumption and leading unsuitable for real-time operations. The Wi-Fi-Based localization system is one of the most widespread approaches for indoor localization due to the fact that Wi-Fi is embedded in most mobile devices without installing extra software or manipulating the hardware.

TABLE I. COMPARISONS OF TECHNICAL SPECIFICATIONS ON RF-BASED COMMUNICATION TECHNOLOGY FOR INDOOR LOCALIZATION.

Specifications	(i) Cellular Communications	(ii) Non-Cellular (Ad-Hoc and Peer-to-Peer Communications)					
		RFID	Bluetooth	Wi-Fi	ZigBee	UWB	LoRa
1. Standard	GSM/GPRS	IEEE 802.15.1	IEEE 802.15.1	IEEE 802.11n	IEEE 802.15.4	IEEE 802.15.6	LoRaWAN
2. Operating Frequency	900/1800 MHz	13.56 MHz	2.4 GHz	2.4/5 GHz	2.4 GHz	3.1GHz-10.6GHz	430/433/868/915 MHz
3. Maximum Distance	30km (LR)	1m (SR)	30m (MR)	50m (MR)	100m (MR)	10m (SR)	5km(UA), 15km(SA), (LR)
4. Data Rate Transfer	10 Mbps (High)	50 Mbps (Low)	1-3 Mbps (Medium)	54 Mbps (High)	250 kbps (Low)	55-410 Mbps (High)	50 kbps (Low)
5. Transmission Current (mA)	500-1000 mA (High)	15 mA (Low)	35 mA (Low)	238 mA (High)	32 mA (Low)	55 c mA (Medium)	25 mA (Low)
6. Operation Time 2000-mAh Battery	2-4 Hr. (SOT)	133 Hr. (LOT)	57 Hr. (LOT)	8.4 Hr. (SOT)	62 Hr. (LOT)	36 Hr. (LOT)	80 Hr. (LOT)

*LR=Long Range, MR=Medium Range, SR=Short Range, UA=Urban Area, SA=Suburban Area, SOT= Short Operation Time, LOT= Short Operation Time

TABLE II. SUMMARY OF LORA COMMUNICATION PERFORMANCE CONFIGURATION IN FINE-TUNE PHYSICAL LAYER.

Configurable Setting	Values	Effects
1. Bandwidth	125…500 kHz	Higher bandwidths allow for transmitting packets at higher data rates)1 kHz = 1 kbps(, but reduce receiver sensitivity and communication range.
2. Spreading Factor	$2^6 \ldots 2^{12} \frac{\text{Chips}}{\text{Symbol}}$	Bigger spreading factors increase the signal-to-noise ratio and hence radio sensitivity, augmenting the communication range at the cost of longer packets and hence a higher energy expenditure.
3. Coding Rate	4/5…4/8	Larger coding rate increase the resilience to interference bursts and decoding error at the cost of longer packets and higher energy expenditure.
4. Transmission Power	-4…20 dBm	Higher transmission powers reduce the signal-to-noise ratio at the cost of an increase in the energy consumption of the transmitter.

The drawback of Wi-Fi-Based localization system is reliance on Wi-Fi location in building and signal attenuation caused by the static environment or movement of furniture and doors, resulting in low-accuracy localization. ZigBee is another wireless technology standard which provides short and medium range communications with low-power consumption but do not require large data throughput. Although it is possible for a communication distance of 100 m. for Line-of-Sight operation, the coverage range for in indoor environments could possibly be only 20m -30m due to obstacles in static indoor environment. As ZigBee operates in the unlicensed ISM bands, it is therefore relatively vulnerable to interference from a wide range of signal types using the same frequency which can disrupt radio communications. In summary, several techniques for the enhancement of indoor localization based on such Bluetooth, Wi-Fi, and ZigBee technologies have been proposed in order to increase accuracy and precision, coverage and resolution, latency, and effects of random errors caused by signal interference and reflections [8]. As a consequence, a hybrid positioning system, which is defined as systems for determining the location by combining several different wireless technologies, have been suggested as an alternative solution for indoor localization quality enhancement [9]

Recently, LoRa, which stands for "Long Range", is a promising long-range wireless communications system, fostered by the LoRa Alliance [10]. LoRa has been designed as a long-lived battery-powered device, where the energy consumption is of paramount importance. Typically, LoRa can be distinctly classified into two layers: (i) a physical layer using the Chirp Spread Spectrum (CSS) radio modulation technique and (ii) a MAC layer protocol (LoRaWAN). The LoRa physical layer, developed by Semtech, allows for long-range, low-power and low-throughput communications. It operates on the 433-, 868- or 915-MHz ISM bands, depending on the region in which it is deployed. The payload of each transmission can range from 2–255 octets, and the data rate can reach up to 50 Kbps when channel aggregation is employed. The modulation technique is a proprietary technology from Semtech. LoRaWAN provides a medium access control mechanism, enabling many end-devices to communicate with a gateway using the LoRa modulation. While the LoRa modulation is proprietary, the LoRaWAN is an open standard being developed by the LoRa Alliance.

This paper therefore studies an indoor localization technique through the utilization of Received Signal Strength Indicator (RSSI) of LoRa Technology. The methodology employs five sets of LoRa nodes and four of which were utilized as statistic nodes, radiating a signal power from 2-meter high from the floor. The receiving node is placed in a particular coordinate on the floor. The RSSI values were employed as inputs for Artificial Neural Network (ANN) for estimation of the coordinate of the receiving node. The LoRa frequency is 915 MHz and the microcontroller is Arduino Pro-Mini that processes all signals with Lithium-Ion Battery.

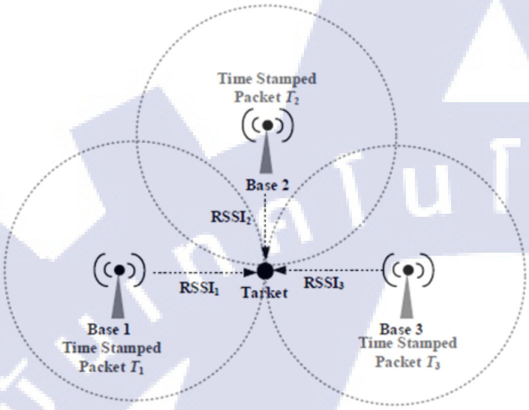

Fig. 1. A generic visualization of indoor positioning techniques with three base stations, demonstrating both RSSI and time stamped packets.

II. Reviews on Typical Indoor Localization Approaches

Several wireless technologies have been realized for indoor localization approaches, depending on performances and also limitation of mathematical models for location estimation. Typically, major performance metrics associated with localization systems involve the following areas, i.e. (i) an accuracy that can be described as an error distance between estimated and actual locations, (ii) The responsiveness that determines speed of updating time of estimated location, (iii) coverage that determined the network coverage under a designated area of localization, (iv) adaptivenes which refers to an ability of the localization system to cope with environmental influence changes that affect to overall system performances, (v) Scalability in which a localization system can potentially operates with a larger number of location requests and a larger coverage, and (iv) cost and complexity, which are on of practical concerns, involving extra infrastructure, additional bandwidth, money, lifetime, weight, energy, and nature of deployed technology. Based upon the above mentioned performances and suitability of localizing environments, this paper particularly summarizes indoor localization approaches with two categories, i.e. proximity and triangulation [11-12].

A. Proximity Detection Approach

Proximity detection is the simplest positioning method for implementing localization of a target. This method provides relative position between a target and a cell of origin, such as GSM, RFID, or Bluetooth, with known position and limited range. Typically, this method detects the target via the nearest position where the strongest signal is received. In recent years, this method has been deployed using beacon with short-range communications. However, the proximity-based method has a high variance which may not satisfy the need for localization.

B. Triangulation

Triangulation utilizes geometric properties of triangles to determine the target location, which typically has two derivations, i.e. angulation and lateration. On the one hand, angulation method refers to as Angle-of-arrival (AoA) method which determines the angle of arrival of the signal receiving from a known location at which it is received at multiple base stations. Geometric relationships can subsequently be utilized in order to estimate the location of the intersection of line angles. Although the angle of signal can be retrieved straightforwardly through directional antenna technology, the angle of stations may not exactly be the angle of received single due to the existence of multi-path and environmental reflections.

On the other hand, lateration method refers to a position determined from distance measurements obtained from multiple reference points. Fig. 1 demonstrates a generic visualization of indoor positioning techniques with three base stations, demonstrating both time stamped packets and RSSI. It can be considered from Fig. 1 that lateration methods can be classified into two types, including (i) time-based triangulation, and (ii) RSSI-based triangulation. General techniques for time-based triangulation are generally Time-of-Arrival (ToA) which directly measures time stamped packet transmitted from base stations or versa vice. Meanwhile, Time Difference of Arrival (TDoA) is a measure between multiple pairs of reference points with known locations and exploits relative time measurements at each receiving node in place of absolute time measurements. Besides, Received Signal Strength (RSS) as also shown in Fig. 1 has been used to represent received signal property. The distance can be obtained and the location can be calculated based on by receive signal strength property.

III. Received Signal Strength

Received Signal Strength Indication (RSSI) typically refers to as a measurement of the power existent in a received radio signal. The RSSI values are generally measured in dBm and have typical negative values ranging from 0 to approximately -120 dBm, which is a noise floor. As wireless Radio Frequency (RF) signals traverse air, a number of effects, such as noises and air resistance, directly affect signal degradation, resulting in attenuation of a received power. Based upon the standard definitions of terms for antennas, i.e. IEEE Standard 145-1993 [13], the Free-Space Path Loss (FSPL) can be modeled as

$$P_R = P_T\left(\frac{\sqrt{G_R}G_T\lambda}{4\pi d}\right)^2 \tag{1}$$

where P_R is a received power, P_T is a transmitted power, G_R is a transmitting antenna gain, G_R is a receiving antenna gain, λ is a signal wavelength, and d is the distance between the two antennas. Eq. (1) can also be described in Decibel (dB) as follows;

$$P_R[\mathrm{dBm}] = P_T[\mathrm{dBm}] - 20\log_{10}(d) - 20\log_{10}\left(\frac{4\pi}{\lambda}\right) \qquad (2)$$

It should be noted that real model of (2) should involve a signal loss caused by shadowing effect, which is a result of fluctuations in measurements due to various disturbances such as interference from transmissions, weather effects or scattering. This paper therefore proposes the RSSI-based triangulation through the use of fingerprint database technique for indoor localization.

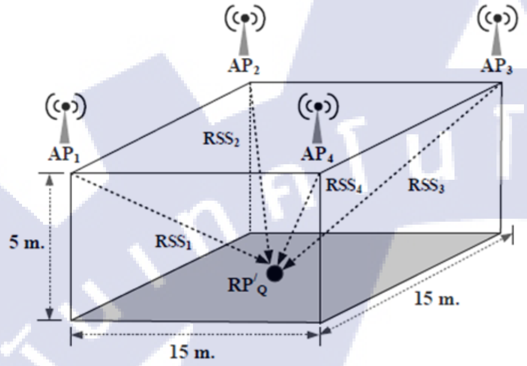

Fig. 2. System model geometry and area coverage, involving four *AP*s and a single target in a reference point RP'_Q.

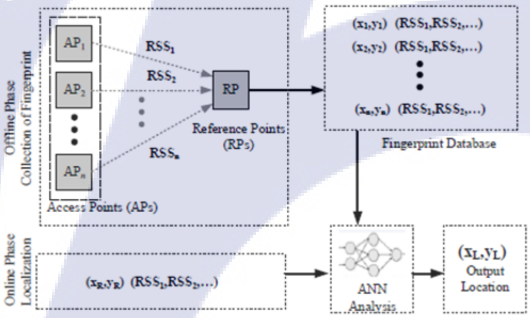

Fig. 3. The overall architecture of the proposed RSSI-based indoor localization using LoRa technology with fingerprinting database.

IV. Proposed RSSI-Based Indoor Localization Using LoRa Technology with Fingerprint Database

Fig. 2 depicts system model geometry and area coverage, involving four *AP*s and a single target in a reference point RP'_Q. The designed system employs four Access Points (*AP*s) which are all LoRa transmitters. A single receiving module RP'_Q is also a LoRa receiver located at a particular Reference Points (*RP*s). The width and length of a floor are 15m. and 15m., respectively, and hence the area is 225 m^2. The height of those four APs is 2m. The coordinate (x,y) is 1m^2. Fig. 3 shows the overall architecture of the proposed RSSI-based indoor localization using LoRa technology with fingerprinting database. It can be considered from Fig.3 that location fingerprinting comprises off-line and the on-line phases. The off-line phase constructs a map for the targeted area, and coordinates of RPs are designated. Subsequently, RSS values received from each *RP* from all *AP*s are collected and stored in a fingerprint database. In the on-line positioning phase, the unknown position of a target is estimated Artificial Neural Network (ANN) which has been trained by a fingerprint database. In this paper, RSS probability distributions of all APs at all *RP*s are required to be stored for training ANN. The fingerprint of the i^{th} *RP*s can be defined as follows;

$$R_i = \begin{bmatrix} P(A_1T_1|L_i) & P(A_2T_1|L_i) & \cdots & P(A_NT_1|L_i) \\ P(A_1T_2|L_i) & P(A_2T_2|L_i) & \cdots & P(A_NT_2|L_i) \\ \vdots & \vdots & \vdots & \vdots \\ P(A_1T_M|L_i) & P(A_2T_M|L_i) & \cdots & P(A_NT_M|L_i) \end{bmatrix} \qquad (3)$$

where A_n, n=1⋯N, is the n^{th} of *AP*, *T* is the measurement of RSS, L_i is i^{th} RP, and *P* can be expressed as follows;

$$P(A_iT_M|L_i) = \frac{C_{T_m}}{N_i} \qquad (4)$$

where N_i is the total number of training samples collected at the i^{th} *RP*, and C_{Tm} is the number of T_m appearing in the training data at the i^{th} *RP*. Consequently, the fingerprint database *D* is given by

$$D = [R_1, R_2, \ldots, R_w] \qquad (3)$$

where *w* is the total number of *RP*s in the coverage area. In addition to fingerprinting database, this work alternatively employ ANN instead of other common techniques such as database matching or search algorithm. The supervised learning ANN with Back-Propagation Learning Algorithm was chosen for training the database *D*. Fig. 4 shows the structure of a realized ANN for determining the location of an output coordinate (x,y). It is apparent in Fig.4 that the four inputs are RSS_1 to RSS_4, which are normalized to be in a region of (0,-1) dBm. The optimized hidden layer comprises 30 nodes and the two output nodes provide the coordinate (x,y).

V. Circuit Designs and Experimental Results

A. Circuit and System Designs

The proposed LoRa module has been designed as a stand-alone device, which can be equipped with other microcontroller. Fig.4 shows the block diagram of the proposed LoRa End-Node. It can be seen from Fig.4 that the end-node comprises a LoRa Module with built-in an antenna. This LoRa module is connected to the Arduino Pro-Mini that processes all signals both inputs and outputs. The power supply system is a Lithium-Ion Batter (3.7V) that connects to a battery charger module TP4056, which supplies a power to a step-down voltage regulator module of 3.3V.

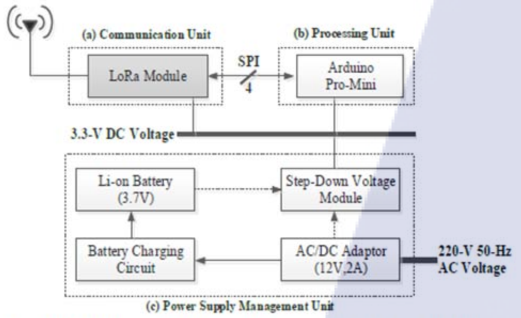

Fig. 4. Block diagram of LoRa module equipped with Arduino Pro-Mini, and Regulator, and a built-in antenna.

TABLE III. TECHNICAL SPECIFICATION OF CIRCUIT MODULES.

Circuit Modules	Specifications
LoRa Chip SX1276/77/78	168 dB maximum link budget +20 dBm - 100 mW constant RF output vs. Supply +14 dBm high efficiency PA Programmable bit rate up to 300 kbps High sensitivity: down to -148 dBm Bullet-proof front end: IIP3 = -11 dBm Excellent blocking immunity Low RX current of 9.9 mA FSK, GFSK, MSK, GMSK, LoRaTM and OOK 127 dB Dynamic Range RSSI
Antenna ANT-RA57-915	890-915MHz, Center Frequency at 915 MHz 2-dBi Gain VSWR ≤ 2 Vertical Polarization 50-Ω Impedance
Arduino Pro-Mini MEGA328P	Operating Voltage at 3.3V or 5V 14 Digital I/O Pins and 6 Analog Input Pins Flash Memory of 32kB SRAM of 2 kB EEPROM of 1 kB

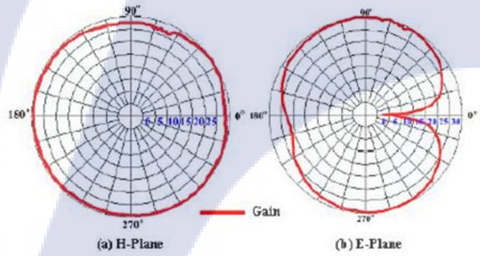

Fig. 5. The radiation pattern of an antenna; (a) H-Plane, (b) E-Plane.

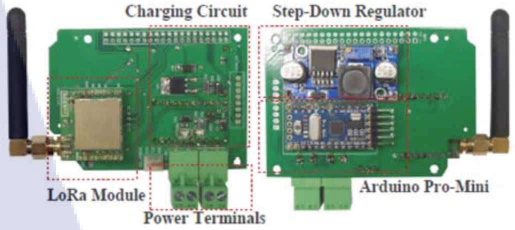

Fig. 6. The assembled two-layer circuit prototype of the LoRa-based communication module with built-in monopole antenna.

Table 3 summarizes technical specifications of circuit modules. The LoRa is apparently not only offers high efficiency of +14 dBm but also minimizing current consumption of 9.9 mA. In particular, the LoRa module provides high dynamic range RSSI of 127 dB with whilst excellent blocking immunity, which is suitable for indoor localization. It is also seen in Table 3 that the antenna is a typical for LoRa communication at a center frequency of 915 MHz and the gain is 2-dBi with a maximum Voltage Standing Wave Ratio (VSWR) of two. In accordance to the antenna, Fig. 5 depicts the radiation pattern of an antenna both in H-plane and E-plane. As the polarization is vertical, the directivity in H-plane provides a full gain of approximately 40 dBi in all

Fig. 7. Test for signal strength coverage area at C-Building of Thai-Nichi Institute of Technology.

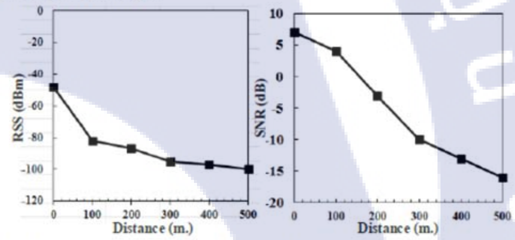

Fig. 8. The measured RSSI in dBm and SNR in dB versus a distance.

direction whilst the gain drops to zero for E-plane at 0°. The experiment shall be carefully considering a vertical polarization in order to receive a RSS properly. Finally, Table 4 also indicates that the Arduino Pro-Mini MEGA328P was chosen as a processing unit with 14 digital I/O pins and 6 analog input pins and sufficient memory for application in indoor localization, i.e. Flash Memory of 32kB, SRAM of 2 kB, and EEPROM of 1 kB. Fig. 6 illustrates the assembled two-layer circuit prototype of the LoRa-based communication module with built-in monopole antenna. As for experiment on indoor localization 5 boards were assembled, four of which will be employed as *APs* and one for *RP*.

B. Evaluations of Reliability of LoRa Communications

Preliminary evaluation of the LoRa communication module was conducted at Thai-Nichi Institute of Technology where the gateway was installed at the 6th floor of C-building with a height of 550 meters. Fig. 7 shows a physical map for testing signal strength with an increment of 100 meters. The performances were investigated by RSSI, which is usually expressed in dBm from 0 to approximately lowest at -120 dBm. In addition, Signal-to-Noise Ratio (SNR) defined as the ratio of signal power to the noise power has also been investigated. Fig. 8 shows plots of measured RSSI in dBm and SNR in dB versus a distance. The RSSI decreased from 0 to around -90 dBm within the first100 meters. From the distance of 100 meters to 500 meters, the values of RSS decreased from -90 dBm to approximately -100 dBm before signal lost. Meanwhile, the SNR is positive till the distance of around 160 meters and the SNR was then decreases to -18 dB at 500 meters. Such results indicate that the LoRa communication is reliable with satisfied SNR values for further implementations. As mentioned earlier, the width and length of a floor are 15m. and 15m., respectively. Therefore, the overall performance is sufficient for indoor localization implementation.

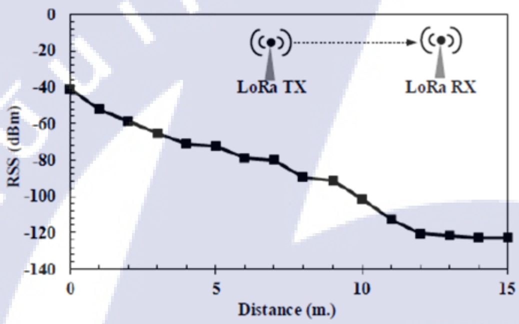

Fig. 9. Plots of RSS versus a distance for one-to-one communication tests.

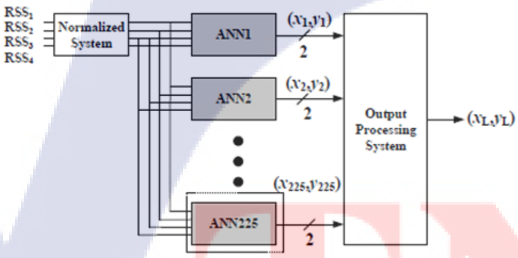

Fig. 10. ANN-Based Indoor Localization with output processing system.

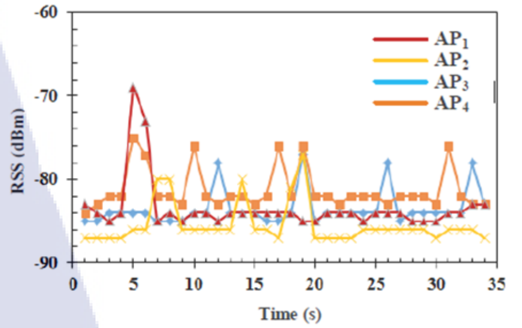

Fig. 11. Examples of a received RSS in dBm of the four APs in time-domain.

C. Experimental Results for Indoor Localizations

The proposed indoor localization system has been conducted based on the system model depicted in Fig.2. First, a one-to-one communication using two LoRa modules was investigated in terms of RSS for evaluating a characteristic curve of RSS values versus a distance as shown in Fig. 9. The plots reveal that the values of RSS decreases from -40dBm to approximately -120dBm over an entire distance range of 15 meters. The characteristics is relatively linear with sufficient different in RSS values, and therefore it can be concluded that the utilization of RSS from LoRa technology is applicable for indoor localization within 15 meters.

Second, each of location in the coverage area was recorded as a fingerprint database, and it was trained by ANN. Fig. 10 shows ANN-Based Indoor Localization with output processing

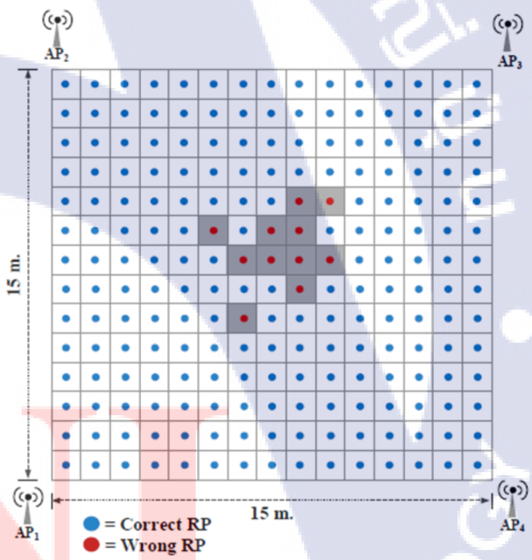

Fig. 12. Results of correct and wrong indoor localization over 15 m².

system. The system comprises 255 module of trained ANN in order to distinguish each location where the output system determines the location. The ANN is a back propagation and each block was trained with customized number of hidden nodes with a golden error of less than 10^{-3}. Activation functions of a hidden layer is a sigmoidal function while the output function is a piecewise-linear function, i.e. $f(x) = 0$ for $x<0$, $f(x) = 0$ for $0<x<1$ and $f(x) = 1$ for $x>1$. The output activation function assists a precise location on the area of experiments.

Third, Fig. 11 depicts Examples of a received RSS in dBm of the four APs in time-domain at a particular location. It can be seen in Fig. 11 that the RSS are relative different. As a result, Fig. 12 illustrates correct and wrong indoor localization over 15 m^2. There are 11 locations that the proposed system cannot be localized and there in a middle of an area. This is because of close values of RSS received from the four APs. Therefore, the error is 4.88%, yielding the accuracy of 95.22%.

VI. CONCLUSIONS

This paper has introduced an indoor localization technique through the use of Received Signal Strength Indicator (RSSI) of LoRa Technology. The LoRa chip from SEMTECH has been implemented on a compact board with built-in antenna. The Arduino microcontroller was employed as a core processor with a step-down switching regulator. Five sets of LoRa nodes were implemented and four of which were utilized as statistic nodes, radiating a signal power from 5-meter high from the floor. The localization has exploited 255 module of trained ANN in order to distinguish each location. The resulting error the error is 4.88%, yielding the accuracy of 95.22%. The result provides satisfactory accuracy with cost-effective and low-power operation as for an alternative for long-range deployments of indoor localization.

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CERTIFICATE

OF PARTICIPATION

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This certificate is to certify

Siratkorn Muekdang.

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