

# Estimation of ToA in Timing Advance mechanism for URLLC in 5G Industrial IoT Networks



By

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# Approval

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# Abstract

In 5G radio access network, emerging machine type communications in industrial automation, smart grids, automotive and other critical applications has increased the importance of accurate distribution of time synchronization reference up to the device/UE level. For instance, executing real-time isochronous operations in collaborating robots, monitoring, and fault localization in smart grids requires ultra-tight synchronization among the devices. To achieve such level of synchronism at the devices, an over-the-air time synchronization procedure must accurately estimate the base station (BS) to UE propagation delays. In this thesis, we use timing advance (TA) mechanism as an estimator for time of arrival (ToA) for adjusting the effect of propagation delay in synchronization procedure. We study the impact of TA binning on propagation delay estimation, and importantly analyze how multipath channels (a true characteristic of Industrial Internet-of-thing (IoT) environments) deteriorates the estimation. Our analysis shows that multipath channels could introduce large errors in synchronization while, averaging multiple consecutive TA values, in static device deployments, brings the errors to an acceptable level, i.e., less than  $1 \mu\text{s}$ , assuming that the BS-UE clock disparity has already been mitigated.

# Dedication

I dedicate this thesis to my father Muhammad Isa Khan, my mother Kausar Parveen and my sisters. Without their constant prayers, this day might never have come.

# Certificate of Originality

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at NUST SEECS or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation and linguistics which has been acknowledged.

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# List of Abbreviations

IIoT	Industrial Internet-of-Things
CPS	Cyber-physical system
PTP	Precision time protocol
RAN	Radio access network
RAT	Radio access technologies
URLLC	Ultra-reliable and low-latency communications
mMTC	Massive machine type communications
eMBB	Enhanced mobile broadband
mmWave	millimeter wave
ToA	Time-of-Arrival
AoA	Angle-of-Arrival
RSSI	Received signal strength intensity
TA	Timing Advance
MSE	Mean square error

# Chapter 1

## Introduction and Background to Thesis

### 1.1 Evolution of 5G

The impending next big thing to happen in cellular technology is the arrival of 5G which will be an improvement to its predecessor cellular network in providing better services to the end systems. [3–7]. Fig. 1.1 shows some of the 5G applications.

The advancements in the certain key enabling technologies of this era, such as, millimeter waves (mmWave), massive connectivity, massive multi-input multi-output (MIMO), new radio access technologies (RAT), software defined networking (SDN), network function virtualization (NFV), scalable Internet of Things (IoT), Big data and mobile cloud computing etc., and their usage will revolutionize the wireless ecosystem of next generation 5G cellular network [8, 9].

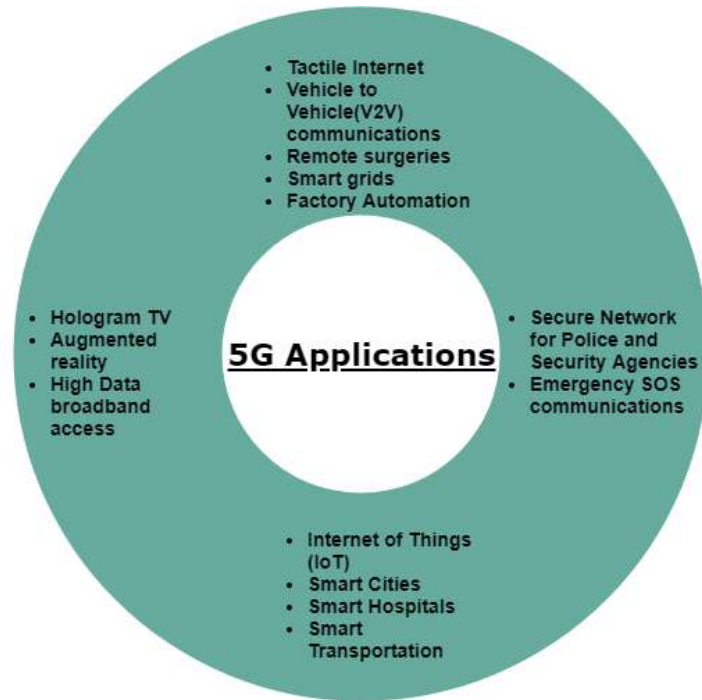


Figure 1.1: Usage of 5G in various applications

### 1.1.1 5G Network Services

5G network service is not only entitled to provide mobile broadband services to end users but it will also provide services in following three broad categories [10]:

- Enhanced mobile broadband (eMBB): 5G network is expected to deliver improved performance than its predecessor cellular networks in terms of wide-area coverage, increased data rate and high mobility to end users.
- Massive machine type communications (mMTC): This service is for mMTC deployment cases in which a large number of devices or sensors are placed in relatively small area i.e. 1,000,000 devices/km square.

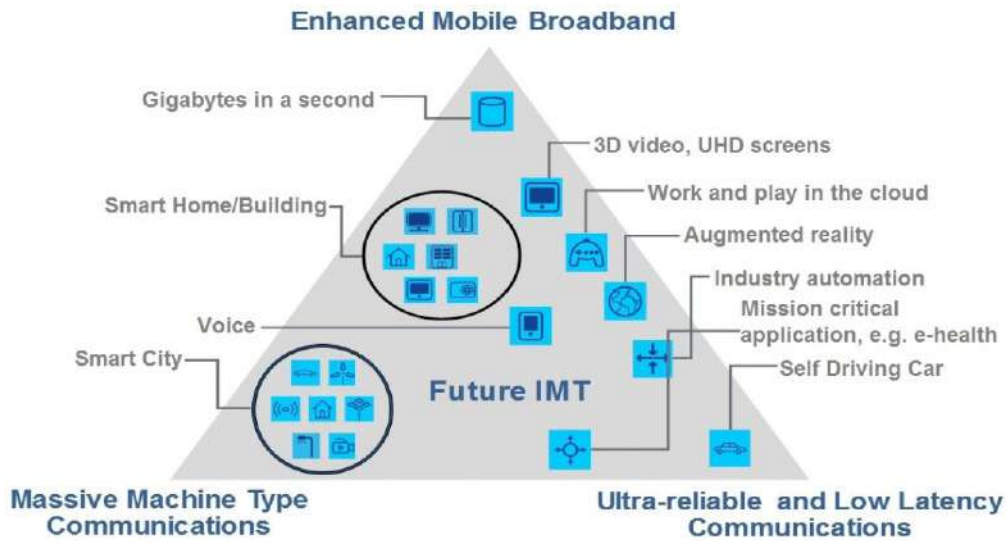


Figure 1.2: 5G services categories and use cases in IMT 2020 [1]

These devices have low cost, long battery life and delay insensitive data.

- Ultra-reliable and low latency communications (URLLC): This service is for those applications which have strict latency and reliability requirements. There is wide range of applications usage cases which have such stringent requirements such as factory automation, tactile internet, smart home, smart transport system etc., as shown in Fig. 1.2.

Next generation 5G networks are entitled to provide these services to end devices for various domain usages such as Internet of Things (IoT). The IoT is a next big technological advancement, the world has ever seen since the deployment of Internet in late 1960s [11]. This enables the computers and human beings to acquire knowledge and communicate with billion of things or devices such as smart actuators/sensors and other end devices connected



to Internet. Eventually, this next revolution in technology better integrates our real time physical world with cyber world. With exponential rise in use of Internet of Things (IoT) devices, new techniques are being devised for providing massive connectivity, low latency and reliable services to satisfy requirements of IoT devices in smart applications. [12]. Diverse IoT application can fully utilize these new class of services to be provided by 5G network after deployment. URLLC and mMTC will serve as the key service enabler for different cases of IoT device usage in smart systems [13].

## 1.2 Industry 4.0

Evolution in industrial development of the modern day industry ecosystem had been going on from last few centuries. Fig. 1.3 shows the evolution in industrial ecosystem for different timelines. First industrial revolution is based on mechanical production plants which runs on water and steam power. This begins at the end of 18th century [14]. Second industrial revolution begins at the start of 20th century. The factory production lines were powered with electrical energy and aided with mass labour. Third industrial revolution begins in the early 1970, where, factory assembly and production lines embraced the new developed electronics based devices and Internet technology. This made the industrial manufacturing process automatic up to certain aspect and reduces the labour cost, resulting in higher revenue. Now the era of next industrial revolution had arrived termed as Industry 4.0, which emphasizes more on smart inter-connectivity, machine-to-machine communications, access to real-time data, better control on new insights and support optimized

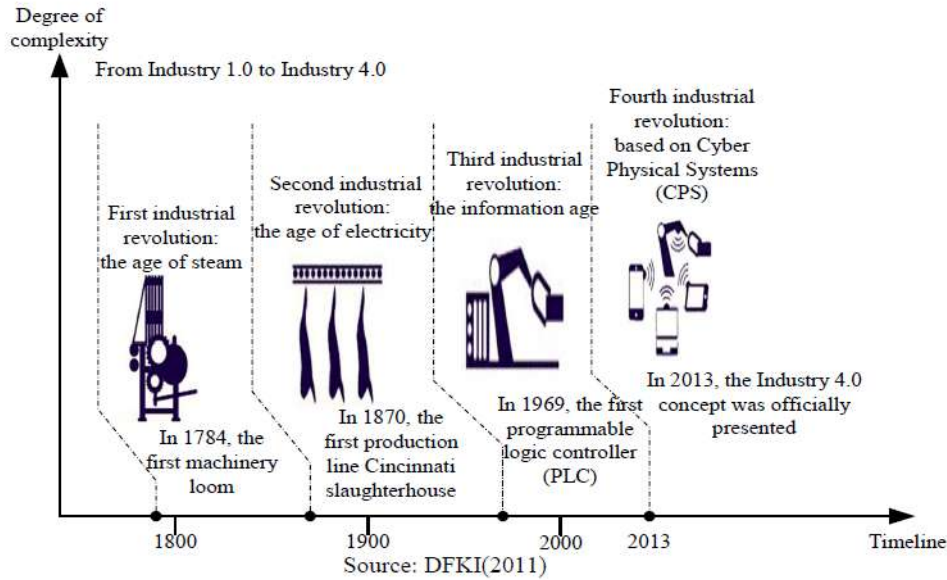


Figure 1.3: History of industrial revolution in different timelines [2]

decision-making process [15].

The manufacturing production line in Industry 4.0 is to be based upon the use of cyber physical system (CPS), in which information from all related aspects such as information monitoring, centralized control, synchronization between cyber computational space and real time factory floor can be closely monitored [16].

### 1.2.1 Rise of Industrial IoT Networks

Recent technological development in deployment of cutting edge technology such as increased computational power of smart sensors or IoT devices, computer networks, cloud and internet, data acquiring techniques etc., has compelled the industry to adopt these systems in their factory ecosystem for

increasing their factory productivity. For bringing next evolutionary transformation regarding the factory automation ecosystem according to vision of Industry 4.0, IoT enabled sensors or actuators and cyber physical system to be deployed in a factory to carry out isochronous operations among all factory entities, resulting in the rise of industrial IoT (IIoT) networks [17, 18]. The key appealing feature in use of IoT devices in industry is that one can access the industrial data of internet enabled end devices anytime through internet and has a centralized control [19]. However, use of IoT devices in industrial scenarios faces certain challenges too. The critical time sensitive industrial applications usually have stringent latency and reliability requirements.

### **1.2.2 URLLC for IIoT**

With exponential rise in the use of Internet of Things (IoT) devices, new techniques are being devised for providing low latency and reliable services. Next generation 5G networks are entitled to provide the ultra-reliable and low latency communication (URLLC) services for various mission critical applications [20]. Recently, URLLC has gained much attention due to increasing demand of low latent and sensitive devices for applications such as factory automation, surgery, robotics, video surveillance, and smart grids [21]. Over the air interface, all these applications have a hard latency requirement of sub millisecond and error rates less than one out of  $10^6$  total packets [22]. Both academia and researchers are investigating ways to overcome challenges that require deterministic communication with low latency and high reliability.

## 1.3 5G Radio Access Network(RAN) for Industrial Wireless Communication

In a cellular radio access network (RAN), base stations give radio access to the end mobile users. It also coordinates the management of radio resources among all the base stations of cellular networks. With evolving cellular networks, RAN also evolved with it to meet the requirements of mobile users. Next generation 5G RAN system is expected to give efficient radio access to meet the services of end systems such as massive connectivity for smartphones, sensors, machines etc., lower end-to-end delay and varying bandwidth requirements [23, 24]. Also, it has to efficiently utilize the conventional microwave spectrum below 6 GHz and millimeter wave (mmWave) bands beyond 28 GHz [25–27]. In industry, different applications have different quality of service (QoS) requirements such as, a CCTV camera data has a large bandwidth requirement to support high resolution video surveillance while, a smart sensor/actuator data has delay intolerant requirements. Therefore, a flexible and unified air interface in such access system will need efficient and sophisticated radio access technologies (RATS) to carry such avalanche amount of data originated from smart phones, IoT devices, sensors and machines. Several industrial applications use cellular technologies for wireless IIoT access points [28]. These industrial applications have witnessed an exponential growth in IoT sensors deployment for carrying out mission critical tasks.

### 1.3.1 Characteristics of Industrial Wireless Propagation Environment

Industrial wireless propagation environment is different from typical outdoor (open or urban) wireless propagation environment. Factory buildings usually are more larger in size than the homes and offices buildings. Building structure is more robust than commercial buildings. Building walls and floors are made up of thick dense material like concrete, cement and usage of iron [29]. Also, there are lot of scatterers and line of sight (LOS) blockage material present inside factory ecosystem, such as, factory machines, cranes, robots etc., which leads to have more multipaths for arriving signals inside factory. This make the industrial wireless propagation environment more harsh than typical urban propagation environment. Also, 5G RAN system has support for both radio waves and mmWaves based spectrum. Hence, in such harsher indoor environment, the channel behavior is different for radio waves and mm waves [30].

## 1.4 Ranging and Localization Techniques

Classical ranging techniques involve the identification and estimation of real world geographical location of an object [31]. Typically, wireless access point systems such as cellular base stations have known location points. They are either obtained through GPS technology or pre-programmed location coordinates installed in their system. End users such as mobile devices, sensors estimate their position from wireless access points through radio signal ex-

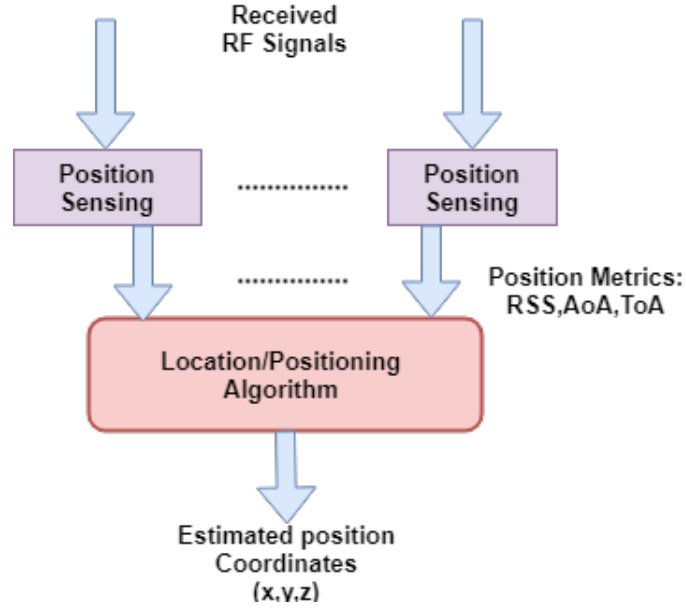


Figure 1.4: General block diagram for location estimation process

changes to know their locations.

Most of the popular geolocation techniques are based on time-of-arrival (ToA), angle-of-arrival (AoA) and received signal strength intensity (RSSI) methods [32]. Fig. 1.4 illustrates the functional block diagram for wireless location estimation techniques.

- Time-of-Arrival (ToA): ToA-based systems extract the location information from an estimate of radio signal propagation time delays between transmitter and receiver. To measure propagation delays, a TOA signal is used. Radio signal travels with speed of light  $c$  in free space. Once the device time delay estimates  $t$  are available, the distance of end device can be measured using  $c/t$ .
- Angle-of-Arrival (AoA): In AoA based system, base stations are equipped

with  $N$  antenna array elements with some fix spacing. They estimate the angle of arrival information from received RF signals and estimate position of mobile from it.

- Received Signal Strength Intensity (RSSI): In RSSI based system, base station estimates the location of mobile nodes from the received signal power strength using the distance-power relationship for wireless propagation of RF signals. Different wireless environments have different path loss factors.

#### 1.4.1 Why ToA based ranging techniques are preferred?

Indoor industrial wireless propagation environment faces severe multipath conditions. In such case, harsh multipath environment severely degrade the geolocation techniques performance. Accurate location of sensors/actuators must be known to 5G RAN system in order to mitigate the propagation delay effects of over-the-air (OTA) allocation of radio resources.

Non-line of sight (NLOS) conditions of multipath environment greatly reduce the reliability and accuracy of AoA based system because it is difficult to retrieve the AoA from incoming received signals [33]. This leaves the usage of ToA and RSSI based techniques in multipath environment. RSSI based techniques suffers greatly from the log normal shadowing and fast fading phenomenon i.e., received power of mobile signal fluctuates considerably. This occurs due to the constructive and destructive addition of arriving multipath received signals. For ToA based system, multipath induces the random pos-

itive bias in estimated location of mobile. The major weakness with RSSI based distance estimation is the assumption that path loss exponent of wireless environment is known. While in actual, path loss exponent of wireless environment changes with nature of different multipath conditions. Also, accuracy of distance estimation from RSSI based techniques cannot be increased by taking average of received power alone to correctly estimate the end device position. Therefore, ToA based ranging techniques are preferred over other geolocation techniques.

## 1.5 ToA based Timing-Advance (TA) mechanism for cellular networks

Cellular networks uses ToA based ranging technique to localize the user positioning in network cell. Every mobile user faces their own location specific propagation delay in wireless environment. To counter the effects of mobile user propagation delay, a timing advance mechanism is deployed by cellular network [34–36]. In this mechanism, user sends ToA signal to cell basestation. Base station extracts distance information from mobile user ToA signal and assigns a discrete TA value to mobile user. On the basis of assigned TA value, mobile user adjusts its data transmission clock to avoid collision of transmitted data with other mobile user at the base station end. This process is called *adaptive frame alignment*.

For a factory automation case, multiple sensors/actuators will communicate with a central access point or basestation over the air. To carry out



isochronous operation between multiple sensors/actuators, the effects of propagation delay must be mitigated. Therefore, tight time synchronization over the air is needed in the next generation 5G RAN system for providing service IIoT networks.

## 1.6 Thesis Motivation

The motivation of this thesis is to develop a new over the air (OTA) robust timing mechanism for industrial IoT networks, to minimize the effects of timing delays in context of providing URLLC services by new 5G radio access network (RAN) system. For this purpose, a ToA-based timing advance (TA) mechanism is proposed and studied for alignment of sensors transmitting data frames with respect to their respective propagation timing delays in industrial wireless environment.

## 1.7 Thesis Contribution

The thesis work presents the following main contributions:

- From URLLC perspective, we propose to use timing advance mechanism for IIoT sensors/actuators in mitigating the propagation delays inside an indoor environment.
- The impact of indoor harsh multipath environment on TA mechanism is carried out to analyze propagation delay errors for sensors location in TA bin.

- We analyze the impact of system bandwidth and averaging multiple TA values on accuracy of sensor's location in several multipath environment.
- The analysis shows that multipath induces large resultant errors in sensor location. By lowering the TA bin size, we obtain significant improvement in minimizing propagation delay errors.

## 1.8 Thesis Organization

The organization of the thesis is presented as follows. Chapter 2 highlights the literature review of the important concepts proposed in this thesis for providing a flow for the readers. In chapter 3, a system model for timing advance mechanism in industrial scenario is developed and industrial multipath model is incorporated to study the impacts of multipath environment. In Chapter 4, we investigate the the performance analysis of the proposed system in terms of single TA value, averaging multiple consecutive TA values, biasness and mean square error (MSE). Chapter 5 discusses the results found during performance analysis of proposed system model. Finally, chapter 6 presents the conclusions and further proposes the future work.

# Chapter 2

## Literature Review

In this section, we highlighted the drivers and challenges related to the ultra tight time synchronization in mission critical industry and put light on some research work done in the related field. Networked bus systems and automation control setups of industry depends upon the IEEE 1588 standard protocol [37]. It is a precision time protocol (PTP) designed for factory real time and isochronous wired transmission. It is a master slave protocol in which a central gateway controller has control command authority over slave end devices. In time synchronization mechanism, the central master controller on receiving a reference clock distributes it among all slave devices. All the end slave devices synchronize themselves with the received master clock reference time. Time sensitive networking (TSN) contains a large number of standards [38]. All of these standards are related to the stringent low latency, ultra reliable and resource management aspects, to support time sensitive applications for industry needs. TSN task group also identifies the critical latency, reliability and jitter requirements of single closed loop

transmission in industrial communication. End to end latency should be less than 10 *msec* with 99.99% reliability and jitter constraint of 1  $\mu$ *sec*. Also synchronization accuracy of 500 *nsec* is needed among the factory machines to carry out seamless isochronous operation.

With the arrival of 5G networks, next generation 5G RAN can meet these time critical industrial requirement in the context of providing URLLC service. But, a time synchronization architecture and mechanism is needed for timing updates over the air (OTA). In [39], the authors proposed timing synchronization architecture over the air for sensors/actuators in industrial environment. They identified the challenges and requirements of most of the factory automation setups. Timing synchronization mechanism over the air should have flexible infrastructure to distribute reference time and absolute synchronization among the devices of factory to tackle the challenges of emerging heterogeneity scenarios of industrial network.

To adjust propagation delay between sensors and base station (BS), timing advance (TA) mechanism has been used. TA is used in Global System for Mobile communications (GSM) and Long-Term Evolution (LTE) cellular system for mitigating the propagation delays between mobile users and BSs. In [40], the author have shown improvement in location estimation of mobile user from its time of arrival (ToA) signal by taking an average of few measurements. With some consecutive TA measurements, mean square error (MSE) is small as compared to the single TA value. But TA mechanism is greatly affected by accuracy of ranging algorithm. Wrong TA values reported to mobile user will have larger errors in adjusting propagation delay leading to high latency. Also for simplicity, authors have used standard Gaussian

distribution for ranging error and no multipath environment is assumed. An Industrial wireless environment are mostly indoor propagation scenario where lots of machineries, concrete walls and scatters are present; thereby posing a harsh multipath conditions for sensors/actuators [30]. Harsh multipath environment greatly affects the ranging and localization process [41].

In this thesis, a timing advance mechanism for IIoT sensor networks is introduced to adjust propagation delays. Sensors send ToA signal to BS for ranging purposes. On the basis of sensors location, TA value is assigned to it for adjusting delay. Alsindi Indoor Ranging Error Model is used [42], which mainly focuses on characterizing the ranging error behavior empirically in harsh multipath environment for ToA-based Ultra-Wideband (UWB) systems.

# Chapter 3

## ToA-based TA System Model

### 3.1 TA Binning Model

We consider an indoor propagation environment scenario which has a single base station (BS) and  $K$  sensors/actuators randomly deployed to carry out mission critical applications. Let  $\mathbb{K} = \{1, 2, 3, \dots, K\}$  be the set of all sensors/actuators. The sensors have the capability to communicate with BS over the air. We assume that the reference clock time of each  $k^{th}$  sensor is synchronized with respect to the BS. TA mechanism is deployed to report each  $k^{th}$  sensor its respective propagation delay. In a radio propagation environment, the speed of waves is assumed constant. Hence, depending upon the symbol time period ( $T_s$ ) of operating cellular system, a set of fixed length TA bins denoted by  $\mathbb{B}_N = \{B_0, B_1, B_2, \dots, B_N\}$  formed by the BS. Let  $t_i$  be the center of TA bin where  $i = \{0, 1, 2, 3, \dots, N\}$ , which is the estimator  $\hat{T}_{act}$  for actual propagation delay,  $T_{act}$ . From [43], it is evident that this estimator is best for  $T_{act}$  in wireless environment. Every  $k^{th}$  sensor has its location

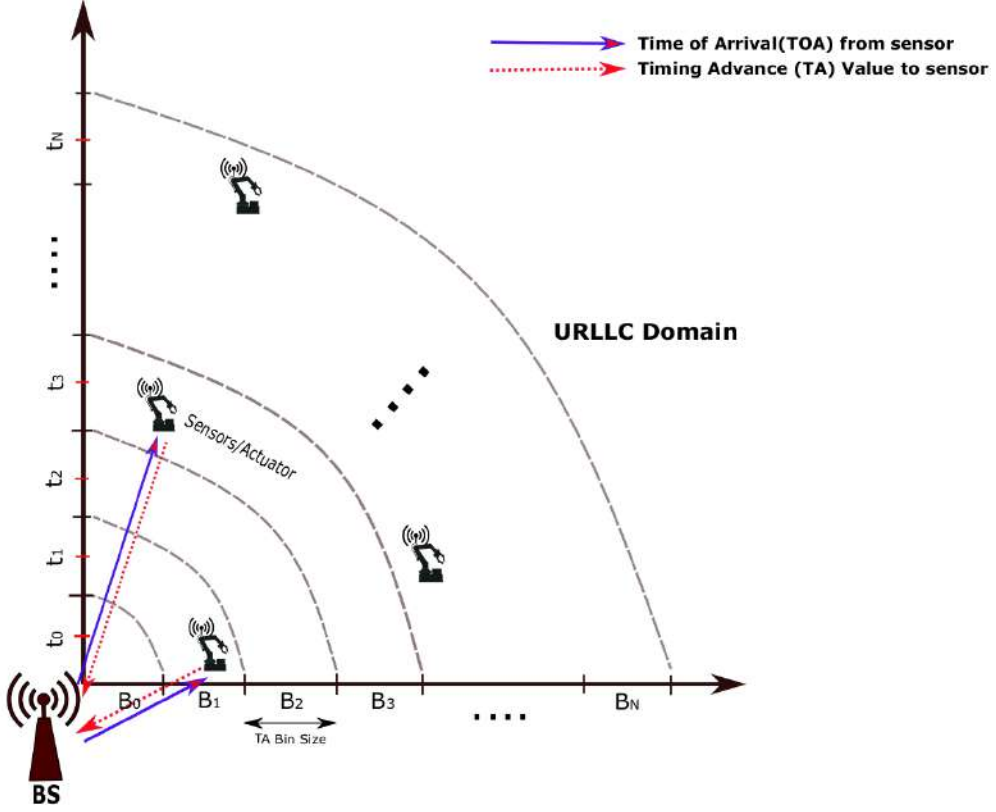


Figure 3.1: Illustration of system model for  $K$  sensors/actuators deployed in indoor environment.

dependent propagation delay.

Depending on  $n^{th}$  TA bin in which  $k^{th}$  sensor location lies, a TA value is assigned to it. From URLLC point of view, each  $k^{th}$  sensor will adjust its reference clock according to its TA value assigned to mitigate the propagation delays. Every discrete TA value is an approximation of the propagation delay which the sensor faces in a wireless environment. All sensors then adjust their reference clock time according to their reported TA value by the BS. For frame time alignment, location of each  $k^{th}$  sensor from BS should be known. As shown in Fig. 3.1, each sensor will send its ToA signal to BS. Without the loss in generality, consider a single sensor scenario for this

study. In the absence of multipath scenario, the BS processor measures the location of sensor from its ToA signal with some random measurement error. The behavior of normalized error,  $\alpha$  is heavily dependent upon the characteristics of wireless propagation environment. For no multipath,  $\alpha$  is simply a standard Gaussian random variable with no biasness.

## 3.2 Multipath Model

For practical indoor harsh multipath environment, error distribution  $\alpha$  may not follow a normal behavior. They even may not be symmetrical errors. Alsindi investigated three different scenarios in four different types of buildings for measurements, i-e, indoor-to-indoor (ITI), roof-to-indoor (RTI) and outdoor-to-indoor (OTI). Those four buildings are located in Worcester, MA (USA). For our indoor propagation study, we focus mainly on ITI scenario. Indoor multipath space is different from outdoor open space. Outdoor multipath structure is mainly composed of a direct path (DP) signal and few non-direct path (NDP) propagated signals resulting from reflection, diffraction and scattering, etc. Hence, for indoor environment, things are different. For ToA-based system, distance estimation process is severely impacted by multipath environment due to addition of random biasness. DP of multipath components is used for ranging purpose. But in most of the cases such as non-line of sight (NLOS) condition, it will not be detectible. Because DP signal is sometimes partially detected or in severe cases, it is completely blocked by some obstacles in indoor environment, hence remained undetected. In that, first NDP signal is used for location estimation of sensor which leads to posi-



tive biasness in ranging mechanism. Note that we are mainly focusing on the presence and absence of DP event and not using the traditional definition of NLOS for cellular communication. This implies that a sensor node and base station separated by wall or any other blockage material doesn't mean that DP will always be absent. But still can be classified as NLOS event and a propagation delay will be induced. By combining the conditions discussed above for indoor environment, the normalized ranging error,  $\alpha$  for a sensor under consideration can be model as,

$$\alpha = \alpha_{\text{MPE}} + \lambda(\alpha_{\text{PDE}} + \eta\alpha_{\text{NDP}}), \quad (3.1)$$

In (3.1),  $\alpha_{\text{MPE}}$  is the normalized multipath error due to presence and absence of DP in LOS conditions,  $\alpha_{\text{PDE}}$  is the normalized propagation delay error added in case when DP signal is partially attenuated, and  $\alpha_{\text{NDP}}$  is the normalized error in case when DP signal is blocked. To differentiate behavior of  $\alpha$  in between LOS and NLOS events for indoor environment, a Bernoulli random variable  $\lambda$  is used, where

$$\lambda = \begin{cases} 0, & \text{LOS} \\ 1, & \text{NLOS} \end{cases} \quad (3.2)$$

The  $\mathbb{P}(\lambda = 0)$  denotes the probability of a sensor node being in LOS condition while  $\mathbb{P}(\lambda = 1)$  denotes the probability of sensor node facing NLOS condition. Similarly to model the presence and blockage of DP event for sensor condition in case of NLOS condition occurs, another Bernoulli random

variable  $\eta$  is used.

$$\eta = \begin{cases} 0, & \text{DP} \\ 1, & \text{NDP} \end{cases} \quad (3.3)$$

Where  $\mathbb{P}(\eta = 0)$  is the probability of DP detection while  $\mathbb{P}(\eta = 1)$  is the probability of DP blockage event occurrence. Table 5.1 shows that for ITI scenario, Fuller and AK have more blockage probability for ToA-based system operating at 500 MHz and 3 GHz band. The model also analyzes the behavior of  $\alpha$  in various multipath conditions. The main goal was to study impact of harsher indoor multipath condition, i.e., NLOS ( $\mathbb{P}(\lambda = 1)$ ) and DP blockage ( $\mathbb{P}(\eta = 1)$ ) event occurrence at same time. So that a reliable TA advance system can be designed which can operate even in such indoor harsh environment. For this condition, Alsindi model confirms that error distribution for  $\alpha$  follows a log-normal with mean  $\mu_\alpha$  and standard deviation  $\sigma_\alpha$ . Its distribution is given as,

$$f(\alpha|\lambda = 1, \eta = 1) = \frac{1}{\sqrt{2\pi}\alpha\sigma_\alpha} \left[ -\frac{(\ln \alpha - \mu_\alpha)^2}{2\sigma_\alpha^2} \right], \quad (3.4)$$

Log-normal parameters in table 5.1 confirms the higher positive biasness due to DP blockage for ranging error in harsh multipath environment. This positive biasness induced by multipath environment will have great impact on accuracy of correct TA value reported to sensor 1 by BS.

# Chapter 4

## Performance Analysis

In this section, the performance analysis of the system is presented in terms of single TA value, averaging multiple consecutive TA values, biasness and mean square error (MSE). We assume a multipath free scenario in the first section, which serves as the benchmark performance. Afterwards, this section is followed by including multipath effects.

### 4.1 Without Multipath (MP) Scenario

In a multipath free environment, the measured sensors location by BS is distributed as Gaussian with mean  $T_{act}$  and standard deviation  $\sigma_{NMP}$ . One of the problems in TA-based systems is that the sensor nodes must infer the  $T_{act}$  from TA value assigned to them which should ideally be free from the measurement errors,  $\sigma_{NMP}$ . In this investigation, we chose the TA bin center,  $t_i$ , as estimator. With ideal conditions, i.e.,  $\sigma_{NMP} < T_s$ , it is sufficient to assume that there is 100% probability that the  $T_{act}$  lies in the  $i^{th}$  selected

bin, i.e.,  $(t_i + T_s/2) \geq T_{act} \geq (t_i - T_s/2)$ . For  $\sigma_{NMP} < T_s$ , the probability of choosing the wrong TA bin becomes substantial. In this case, probability of assigning measured value to  $i^{th}$  bin is given by,

$$\mathbb{P}_i(T_{act}, \sigma_{\alpha_{NMP}}) = \mathbb{P}(bin_i | \sigma_{\alpha_{NMP}}, T_{act}) = \frac{1}{2} \left\{ \operatorname{erf} \left[ \frac{t_i - (T_{act} - T_s/2)}{\sqrt{2\sigma_{\alpha_{NMP}}^2}} \right] - \operatorname{erf} \left[ \frac{t_i - (T_s/2 - T_{act})}{\sqrt{2\sigma_{\alpha_{NMP}}^2}} \right] \right\}, \quad (4.1)$$

where  $\operatorname{erf}(\cdot)$  is the error function.

In most of the cases, an offset error may occur since continuous range of  $T_{act}$  is mapped onto discrete distributions of  $t_i$ . When a wrong TA bin is selected, at least  $T_s/2$  amount of error is added. In such a case, the resultant error becomes much larger. Thereby, affecting the accuracy of sensor node location. To reduce large resultant errors, one of the simple solutions is averaging two or more multiple consecutive TA values that are reported by the system for a given  $T_{act}$ . This not only reduces an offset error but also minimizes the mean square error (MSE). The TA distribution follows a multinomial behavior where the bin occupancies for this distribution depends on  $T_{act}$  of a sensor node. For this  $T_{act}$ , the mean of  $n$  measurements sampled from TA distribution also follows a multinomial distribution. We assume that each measurement is explicitly independent of others. Therefore, the first moment and second moment of measurement is given by,

$$\mathbb{E}(\hat{t}) = \sum_{i=1}^n \mathbb{P}_i t_i, \quad (4.2)$$

$$\mathbb{E}(\bar{t}^2) = \sum_{i=1}^n \mathbb{P}_i t_i^2, \quad (4.3)$$

Since, bin center  $t_i$  is assigned a TA value, therefore, there will be,  $T_{act}$ , dependent bias  $b(T_{act})$  present with expectation value as,

$$b(T_{act}) = \mathbb{E}(T_{act} - \bar{t}) = T_{act} - \left( \sum_{i=1}^n \mathbb{P}_i t_i \right), \quad (4.4)$$

For  $n$  measurements, second central moment or variance of estimator is given by,

$$Var(\bar{t}) = \frac{1}{m} \left[ \sum_{i=1}^n \mathbb{P}_i t_i^2 - \left( \sum_{i=1}^n \mathbb{P}_i t_i \right)^2 \right], \quad (4.5)$$

Since variance of estimator only describes random fluctuation of estimated values about its mean, however, due to presence of bias, this is not the complete description of error. We use MSE to evaluate the estimator performance. MSE is given as,

$$\langle MSE \rangle = b^2(T_{act}) + Var(\bar{t}), \quad (4.6)$$

Since  $T_{act}$  is unknown for given sensor node, we must use population-weighted average MSE [43]:

$$\langle MSE \rangle = \int [b^2(T_{act}) + Var(\bar{t})] \times \rho(T_{act}) dT_{act}, \quad (4.7)$$

Where  $\rho(T_{act})$  is assumed uniform population density in  $T_{act}$ .

## 4.2 With Indoor Multipath (MP) Scenario

From (3.4), it is evident that normalized ranging error ( $\alpha$ ) for indoor multipath environment follows log-normal behavior. By studying the pdf for given parameters in table 5.1, it is observed that different environment shows varying tail behavior. Nature of multipath environment dictates the heaviness of pdf tail. The heavier the tail of pdf is, the more ranging error occurs for sensor 1 in multipath environment. We incorporated log-normal estimated parameters of AK NLOS and Fuller NLOS into our proposed scheme and studied the impact of harsh multipath on TA system for sensors. Estimator performance is also analyzed for multipath environment in terms of (4.1) to (4.7).

# Chapter 5

## Results and Discussions

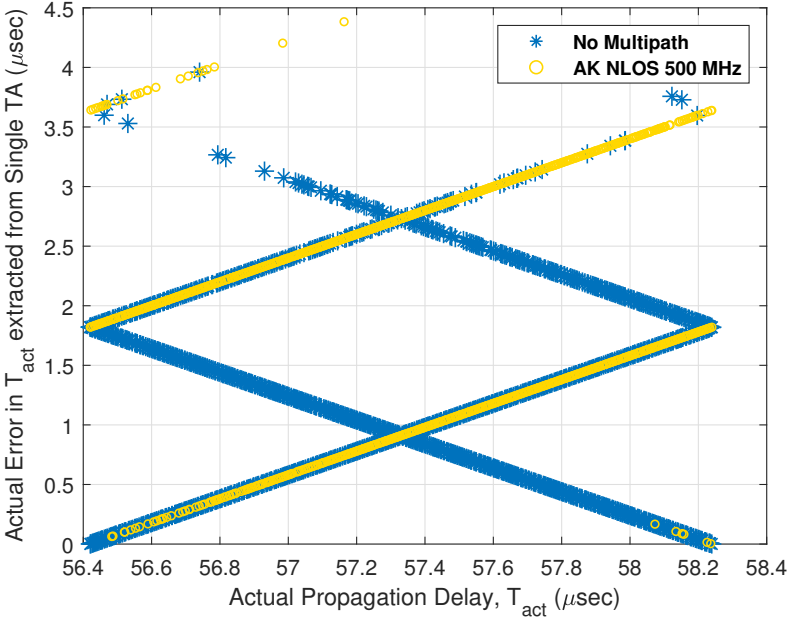
Table 5.1: Parameters for ITI NDP event conditions,  $\mathbb{P}(\lambda = 1)$  and  $(\mathbb{P}(\eta = 1))$

Environment	500 MHz				3 GHz			
	$\mathbb{P}(\eta = 0)$	$\mathbb{P}(\eta = 1)$	$\mu_\alpha$	$\sigma_\alpha$	$\mathbb{P}(\eta = 0)$	$\mathbb{P}(\eta = 1)$	$\mu_\alpha$	$\sigma_\alpha$
Norton (NLOS)	0.96	0.4	-3.13	0.62	0.83	0.17	-4.29	0.45
Fuller (NLOS)	0.1	0.90	-1.68	0.88	0.2	0.98	-1.90	1.13
Schussler	0.89	0.11	-1.59	0.49	0.87	0.13	-2.72	0.53
AK (NLOS)	0.39	0.61	-2.17	0.45	0.32	0.68	-2.89	0.81

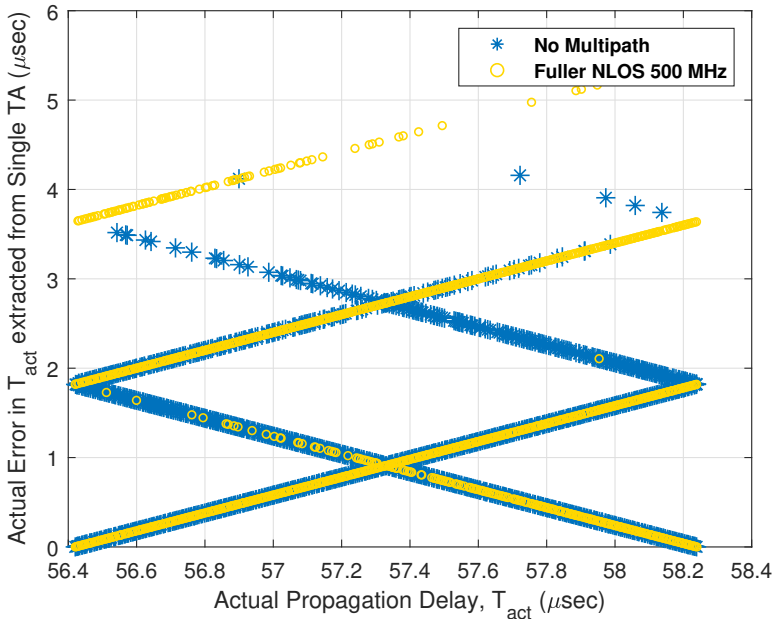
In this chapter, performance of proposed scheme for sensors/actuators is investigated via Monte-Carlo simulations on Matlab<sup>®</sup> 2018a.

### 5.1 Propagation delay errors for single TA value and averaging multiple TA values

For GSM cellular system, symbol time ( $T_s$ ) is 3.64  $\mu sec$ . For this  $T_s$ , bin size is 546 m radial distance and TA numbers ranges from 0-63. We show results for single and three consecutive measured TA values. This particular system is operating at 500 MHz bandwidth. NDP event parameters for AK NLOS



(a)



(b)

Figure 5.1: Actual error in sensor 1 propagation delay extracted from single TA (a) For AK NLOS (b) For Fuller NLOS



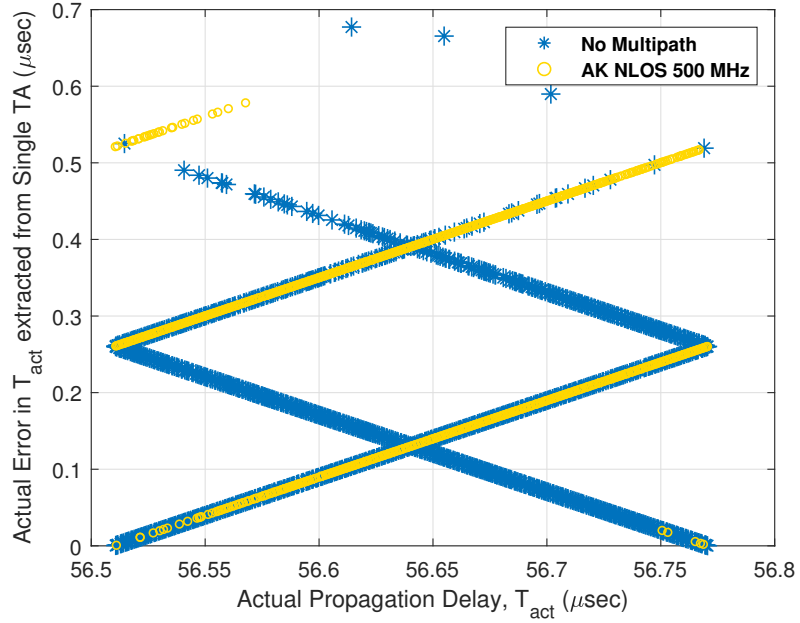
and Fuller NLOS is taken from table 5.1.

From URLLC point of view, scales of all figures are in terms of time ( $\mu sec$ ). Fig. 5.1 shows results for actual error in propagation delay ( $T_{act}$ ) extracted from single TA value in multipath environment. It is evident that multipath environment badly impacts the sensor 1 location accuracy. Thus, leading to high errors in propagation delay. These patterns in results arise because of conversion from continuous range of location values inside single TA bin to discrete TA value. It can be seen from 5.1 that AK NLOS multipath environment has more positive biasness in actual errors than Fuller NLOS while Fuller NLOS has high errors due to reporting wrong TA value.

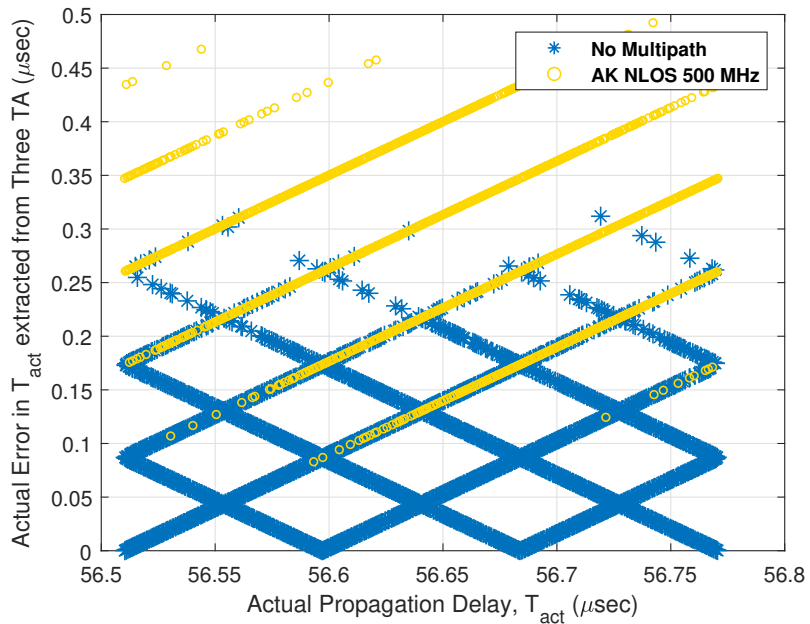
For LTE cellular system,  $T_s$  is 32.6  $nsec$ . Bin size for this  $T_s$  is at 78 m radial distance. TA numbers ranges from 0-1282. Fig. 5.2 and Fig. 5.3 reveals actual errors for single TA and three consecutive TA values in AK and Fuller multipath environment. Reducing bin size from 546 m to 78 m considerably reduces actual error in propagation delay of sensor 1 for multipath environment. Moreover, improvement in TA system occurs for taking average of more than one consecutive TA values. From Fig. 5.1, Fig. 5.2 and Fig. 5.3, it is observed that change in  $\mu_\alpha$  of log-normal ranging error has an impact on positive biasness in actual delay errors while change in  $\sigma_\alpha$  impacts the actual error in terms of reporting wrong TA value.

## 5.2 Impact of System Bandwidth

Fig. 5.4 depicts the impact of system bandwidth on actual propagation delay error in AK and Fuller multipath environment. From Table 1, it is evident

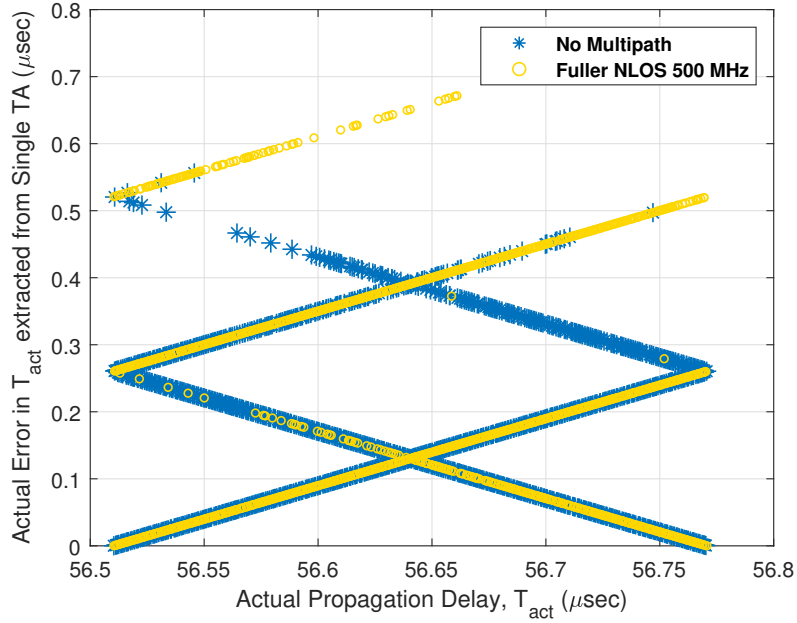


(a)

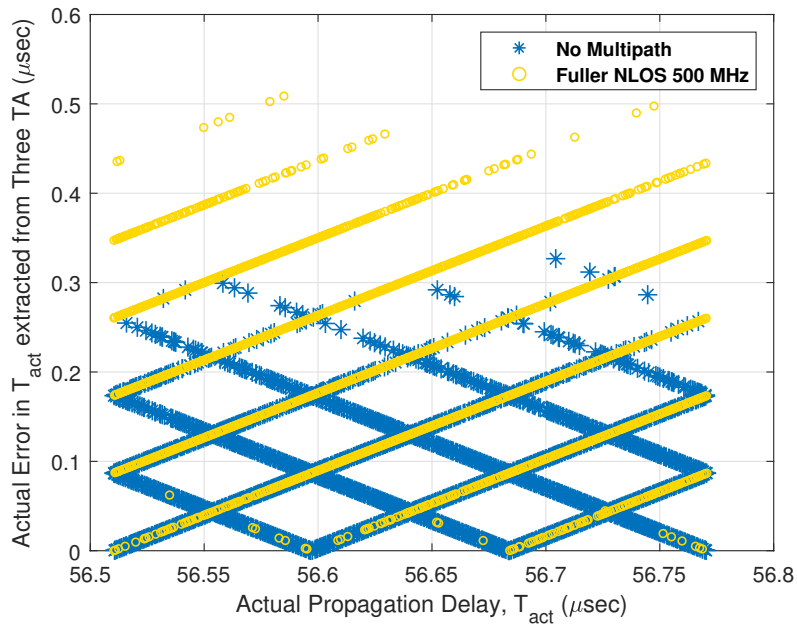


(b)

Figure 5.2: Actual error in sensor 1 propagation delay for AK NLOS multipath environment with TA bin size 78 m (a) Using single TA (b) Using three consecutive TA

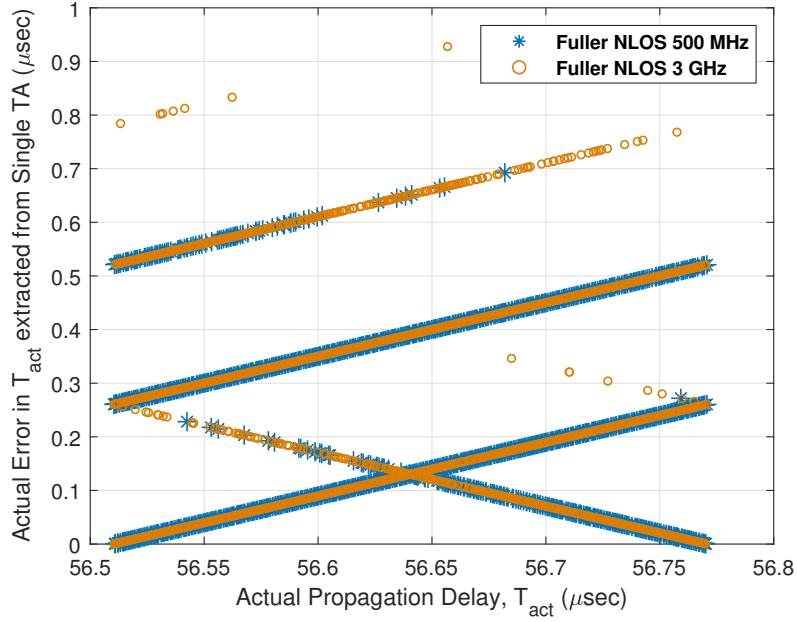


(a)

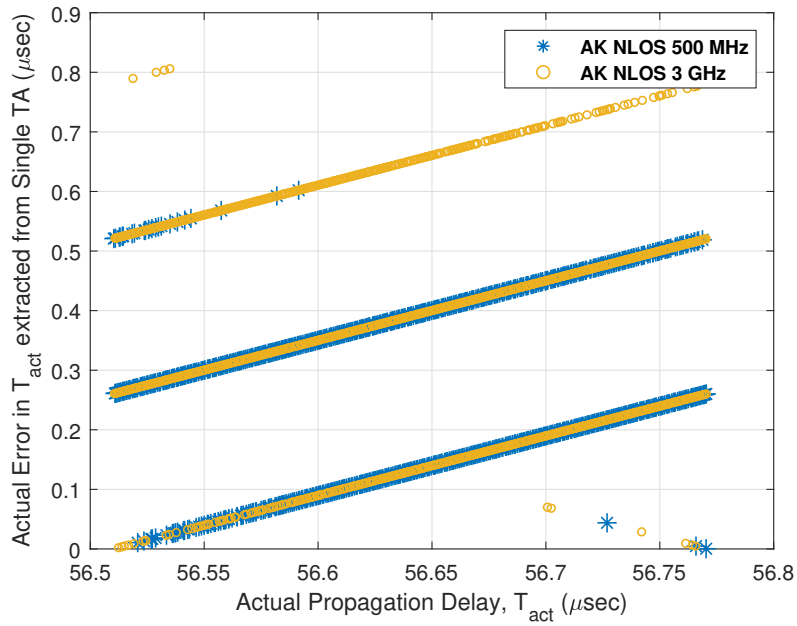


(b)

Figure 5.3: Actual error in sensor 1 propagation delay for Fuller NLOS multipath environment with TA bin size 78 m (a) Using single TA (b) Using three consecutive TA



(a)



(b)

Figure 5.4: Impact of system bandwidth on actual propagation delay for sensor 1 with TA bin size 78 m (a) For AK NLOS (b) For Fuller NLOS

that increasing system bandwidth decreases  $\mu_\alpha$  and increases  $\sigma_\alpha$ . Without loss of generality, it is observed from 5.4 that increasing system bandwidth from 500 MHz to 3GHz leads to increase in actual delay errors for sensor 1.

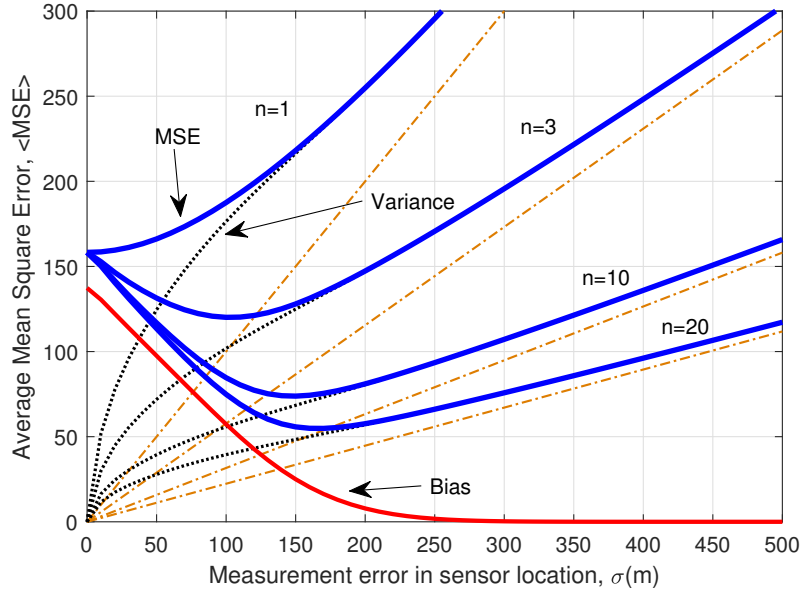
## 5.3 Performance of estimator in terms of MSE

In this section, we analyzed the performance of proposed estimator for sensor 1 in multipath environment to study its impacts on accuracy of location estimation. Two TA bin cases had been taken for performance study.

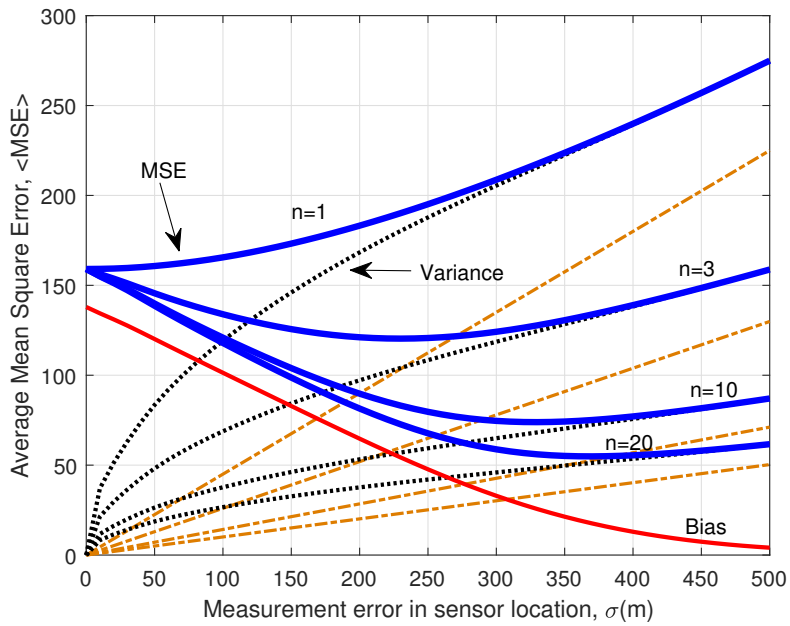
### 5.3.1 With TA bin size 546 m

Fig. 5.5(a) shows the performance of estimator in multipath free environment, in terms of MSE and measurement error ( $\sigma(m)$ ) for sensor 1 with system operating at 500 MHz band. For  $\sigma = 0$ , there is no improvement in MSE over averaging multiple  $n$  measured consecutive TA values.

But increase in measurement error up to 200 m decreases MSE for increasing  $n$ . But beyond 200 m, we dont get any reduction in MSE for large values of  $n$ . Therefore, an optimum value of  $\sigma$  exists for certain specific  $n$  for which we get less MSE ,such as, for  $n=20$ , we get lowest MSE at optimum  $\sigma$  value of 150 m. Ignoring the effects of biasness, variance is plotted using (4.5). It approaches MSE curve for  $\sigma$  greater than 350 m. The effects of two error components on MSE is also shown. Bias decreases for increase in  $\sigma$  and becomes zero at center of TA bin. It doesnt change with averaging.



(a)



(b)

Figure 5.5: Population-averaged delay error for sensor 1 as function of  $\sigma(m)$  and  $n$  with TA bin size 546 m (a) For No Multipath (b) For Multipath

While, raw random measurement error  $\sigma/m$  shown by dash-dotted curve decreases with increasing  $n$ . For increasing  $\sigma$ , random measurement error increases while bias decreases, averaging multiple TA values shows reduction in MSE. Therefore, we can use the statistical technique known as stochastic resonance to improve the average MSE in multipath environment. In stochastic resonance, addition of small noises leads to better chance of signal detection which is otherwise below detection threshold. It is observed from Fig. 5.5(a) that at large values of  $\sigma$ , MSE and variance curves asymptotically approaches the  $\sigma/m$  curve. Thus for the case of sensor 1 in multipath free environment, we see that optimum value of MSE is obtained for increase in  $\sigma$  and averaging  $n > 1$  TA values. But beyond 200 m, no gain in reduction of MSE is observed. Fig. 5.5(b) shows the estimator performance in multipath rich environment. We get less gain in MSE improvement for  $n$  greater than three. Also, bias exists over the whole TA bin.

### 5.3.2 With TA bin size 78 m

Fig. 5.6 shows the performance of estimator in multipath rich environment, in terms of MSE and measurement error ( $\sigma(m)$ ) for sensor 1 with system operating at 500 MHz band. It is evident from Fig. 5.6, that reducing TA bin size from 546 m to 78 m had brought significant improvement in MSE reduction.

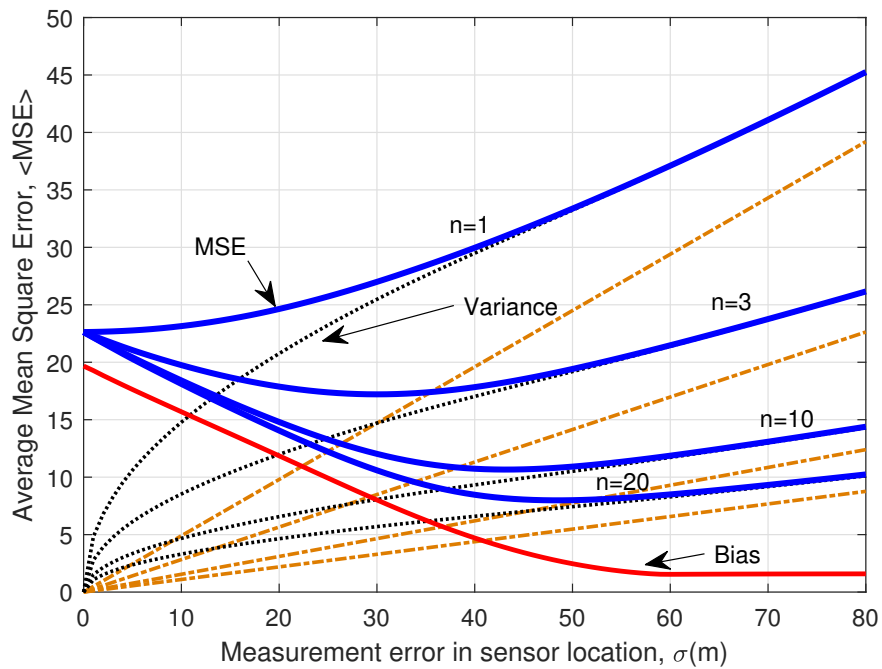


Figure 5.6: Population-averaged delay error for sensor 1 in multipath environment as function of  $\sigma(m)$  and  $n$  with TA bin size 78 m



# Chapter 6

## Conclusion & Future Works

### 6.1 Concluding notes

In this thesis, we have studied TA based scheme for IIoT scenario to mitigate the propagation delay in indoor multipath environment. For indoor harsh multipath environment, we used the Alsindi indoor ranging model. We also evaluated the performance of estimator for multipath environment in terms of bias, variance and MSE. The simulation results show that multipath environment certainly impacts the propagation delay errors for TA-based system. We conclude the thesis as following:

1. We had analyzed resultant error due to reporting single wrong TA value for a given stationary sensor ToA signal. As discrete TA value is just an approximation of propagation delay or ToA value between sensor and BS, each TA value corresponds to a continuous range of ToA values in single bin. This leads to resultant error for a given sensor location. We had shown that averaging multiple TA values for sensor location leads

to reduction in resultant error due to reporting wrong TA value. Thus, increasing the accuracy of estimated sensor propagation time delay.

2. We also had analyzed the resultant propagation delay error for various bin sizes ,i.e, GSM bin size and LTE bin size. GSM bin size is 546 m and LTE bin size is 78 m. It has been observed that decreasing TA bin size brings improvement in reducing errors for sensor's propagation delay.
3. Increasing system bandwidth also impacts the resultant error in severe way by increasing mean and variance of normalized ranging error. This leads to increase in resultant error due to positive biasness and due to wrong TA value assignment.
4. Multipath decreases the MSE performance of estimator. The gain obtained in reducing resultant errors due to averaging multiple TA values also gets impacted by harsh multipath effects.

## 6.2 Future Works

This is just the start of initial work on 5G network providing URLLC services to the mission critical industrial applications. To realize the full potential of over-the-air timing synchronization architecture for next generation 5G RAN system to satisfy needs of stringent delay and reliability driven applications, all key drivers and challenges must be properly addressed and taken care of. As a future work, finding an optimum TA bin size to reduce propagation delay for over-the-air (OTA) based TA scheme in IIoT sensors/actuators

networks can be studied. Also, increasing system bandwidth has impact on normalized ranging error which in turn increased the resultant error. A new physical layer specification for 5G layout plan has a bandwidth numerology architecture to support variable bandwidth and backward compatibility with previous cellular networks. This numerology architecture can be studied with respect to timing advance mechanism.

# Bibliography

- [1] M. Series, “IMT Vision–Framework and overall objectives of the future development of IMT for 2020 and beyond,” 2015.
- [2] K. Zhou, T. Liu, and L. Zhou, “Industry 4.0: Towards future industrial opportunities and challenges,” in *2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*. IEEE, 2015, pp. 2147–2152.
- [3] J. G. Andrews, S. Buzzi, W. Choi, S. V. Hanly, A. Lozano, A. C. Soong, and J. C. Zhang, “What will 5G be?” *IEEE Journal on selected areas in communications*, vol. 32, no. 6, pp. 1065–1082, 2014.
- [4] S. K. Routray and K. Sharmila, “4.5 G: A milestone along the road to 5G,” in *2016 International Conference on Information Communication and Embedded Systems (ICICES)*. IEEE, 2016, pp. 1–6.
- [5] M. Jaber, M. A. Imran, R. Tafazolli, and A. Tukmanov, “5G backhaul challenges and emerging research directions: A survey,” *IEEE access*, vol. 4, pp. 1743–1766, 2016.

- [6] Y. Tao, L. Liu, S. Liu, and Z. Zhang, "A survey: Several technologies of non-orthogonal transmission for 5G," *China Communications*, vol. 12, no. 10, pp. 1–15, 2015.
- [7] R. I. Ansari, C. Chrysostomou, S. A. Hassan, M. Guizani, S. Mumtaz, J. Rodriguez, and J. J. Rodrigues, "5G D2D networks: Techniques, challenges, and future prospects," *IEEE Systems Journal*, no. 99, pp. 1–15, 2017.
- [8] I. F. Akyildiz, S. Nie, S.-C. Lin, and M. Chandrasekaran, "5G roadmap: 10 key enabling technologies," *Computer Networks*, vol. 106, pp. 17–48, 2016.
- [9] S. Zeb, Q. Abbas, S. A. Hassan, A. Mahmood, R. Mumtaz, S. M. Hassan Zaidi, S. Ali Raza Zaidi, and M. Gidlund, "NOMA Enhanced Backscatter Communication for Green IoT Networks," in *2019 16th International Symposium on Wireless Communication Systems (ISWCS)*, 2019, pp. 640–644.
- [10] M. Shafi, A. F. Molisch, P. J. Smith, T. Haustein, P. Zhu, P. De Silva, F. Tufvesson, A. Benjebbour, and G. Wunder, "5G: A tutorial overview of standards, trials, challenges, deployment, and practice," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 6, pp. 1201–1221, 2017.
- [11] A. H. Ngu, M. Gutierrez, V. Metsis, S. Nepal, and Q. Z. Sheng, "IoT middleware: A survey on issues and enabling technologies," *IEEE Internet of Things Journal*, vol. 4, no. 1, pp. 1–20, 2017.

- [12] M. R. Palattella, M. Dohler, A. Grieco, G. Rizzo, J. Torsner, T. Engel, and L. Ladid, “Internet of things in the 5G era: Enablers, architecture, and business models,” *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 3, pp. 510–527, 2016.
- [13] L. Wan, Z. Guo, Y. Wu, W. Bi, J. Yuan, M. Elkashlan, and L. Hanzo, “4G\5G Spectrum Sharing: Efficient 5G Deployment to Serve Enhanced Mobile Broadband and Internet of Things Applications,” *ieee vehicular technology magazine*, vol. 13, no. 4, pp. 28–39, 2018.
- [14] Y. Lu, “Industry 4.0: A survey on technologies, applications and open research issues,” *Journal of Industrial Information Integration*, vol. 6, pp. 1–10, 2017.
- [15] M. Hermann, T. Pentek, and B. Otto, “Design principles for industrie 4.0 scenarios,” in *System Sciences (HICSS), 2016 49th Hawaii International Conference on*. IEEE, 2016, pp. 3928–3937.
- [16] J. Lee, B. Bagheri, and H.-A. Kao, “A cyber-physical systems architecture for industry 4.0-based manufacturing systems,” *Manufacturing letters*, vol. 3, pp. 18–23, 2015.
- [17] A. Gilchrist, *Industry 4.0: the industrial internet of things*. Apress, 2016.
- [18] F. Jameel, M. A. Javed, D. N. Jayakody, and S. A. Hassan, “On secrecy performance of industrial Internet of things,” *Internet Technology Letters*, vol. 1, no. 2, p. e32, 2018.

- [19] M. Wollschlaeger, T. Sauter, and J. Jasperneite, “The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0,” *IEEE Industrial Electronics Magazine*, vol. 11, no. 1, pp. 17–27, 2017.
- [20] C.-P. Li, J. Jiang, W. Chen, T. Ji, and J. Smee, “5G ultra-reliable and low-latency systems design,” in *Networks and Communications (Eu-CNC), 2017 European Conference on*. IEEE, 2017, pp. 1–5.
- [21] M. Bennis, M. Debbah, and H. V. Poor, “Ultra-reliable and low-latency wireless communication: Tail, risk and scale,” *arXiv preprint arXiv:1801.01270*, 2018.
- [22] I. WP5D, “Minimum requirements related to technical performance for IMT-2020 radio interface (s),” 2017.
- [23] T. O. Olwal, K. Djouani, and A. M. Kurien, “A survey of resource management toward 5G radio access networks,” *IEEE Communications Surveys & Tutorials*, vol. 18, no. 3, pp. 1656–1686, 2016.
- [24] M. S. Omar, S. A. Hassan, H. Pervaiz, Q. Ni, L. Musavian, S. Mumtaz, and O. A. Dobre, “Multiobjective optimization in 5G hybrid networks,” *IEEE Internet of Things Journal*, vol. 5, no. 3, pp. 1588–1597, 2018.
- [25] J.-C. Guey, P.-K. Liao, Y.-S. Chen, A. Hsu, C.-H. Hwang, and G. Lin, “On 5G radio access architecture and technology [industry perspectives],” *IEEE Wireless Communications*, vol. 22, no. 5, pp. 2–5, 2015.

- [26] R. I. Ansari, H. Pervaiz, C. Chrysostomou, S. A. Hassan, A. Mahmood, and M. Gidlund, “Control-Data Separation Architecture for Dual-Band mmWave Networks: A New Dimension to Spectrum Management,” *IEEE Access*, vol. 7, pp. 34 925–34 937, 2019.
- [27] R. I. Ansari, H. Pervaiz, S. A. Hassan, C. Chrysostomou, M. A. Imran, S. Mumtaz, and R. Tafazolli, “A New Dimension to Spectrum Management in IoT Empowered 5G Networks,” *IEEE Network*, 2019.
- [28] S. Mumtaz, A. Alsohaily, Z. Pang, A. Rayes, K. F. Tsang, and J. Rodriguez, “Massive Internet of Things for industrial applications: Addressing wireless IIoT connectivity challenges and ecosystem fragmentation,” *IEEE Industrial Electronics Magazine*, vol. 11, no. 1, pp. 28–33, 2017.
- [29] M. Cheffena, “Industrial wireless sensor networks: channel modeling and performance evaluation,” *EURASIP Journal on Wireless Communications and Networking*, vol. 2012, no. 1, p. 297, 2012.
- [30] M. Cheffena, “Industrial wireless communications over the millimeter wave spectrum: opportunities and challenges,” *IEEE Communications Magazine*, vol. 54, no. 9, pp. 66–72, 2016.
- [31] G. M. Djuknic and R. E. Richton, “Geolocation and assisted GPS,” *Computer*, vol. 34, no. 2, pp. 123–125, 2001.
- [32] K. Pahlavan, X. Li, and J.-P. Makela, “Indoor geolocation science and technology,” *IEEE Communications Magazine*, vol. 40, no. 2, pp. 112–118, 2002.



- [33] C. Gentile, N. Alsindi, R. Raulefs, and C. Teolis, “Ranging and localization in harsh multipath environments,” in *Geolocation Techniques*. Springer, 2013, pp. 17–57.
- [34] T. Kos, M. Grgic, and G. Sisul, “Mobile user positioning in GSM/UMTS cellular networks,” in *Proceedings ELMAR 2006*. IEEE, 2006, pp. 185–188.
- [35] S. Kanchi, S. Sandilya, D. Bhosale, A. Pitkar, and M. Gondhalekar, “Overview of LTE-A technology,” in *2013 IEEE global high tech congress on electronics*. IEEE, 2013, pp. 195–200.
- [36] L. Jarvis, J. McEachen, and H. Loomis, “Geolocation of LTE subscriber stations based on the timing advance ranging parameter,” in *2011-MILCOM 2011 Military Communications Conference*. IEEE, 2011, pp. 180–187.
- [37] K. B. Lee and J. Eldson, “Standard for a Precision Clock Synchronization Protocol for Networked Measurement and Control Systems,” in *2004 Conference on IEEE 1588, Standard for a Precision Clock Synchronization Protocol for Networked Measurement and Control Systems*, 2004.
- [38] I. S. Association *et al.*, “IEEE Std 802.1 AS-2011, IEEE Standard for Local and Metropolitan Area Networks Timing and Synchronization for Time-Sensitive Applications in Bridged Local Area Networks,” *Mar*, vol. 30, p. 292, 2011.

- [39] A. Mahmood, M. I. Ashraf, M. Gidlund, and J. Torsner, “Over-the-Air Time Synchronization for URLLC: Requirements, Challenges and Possible Enablers,” in *2018 15th International Symposium on Wireless Communication Systems (ISWCS)*. IEEE, 2018, pp. 1–6.
- [40] G. P. Yost and S. Panchapakesan, “Improvement in estimation of time of arrival (TOA) from timing advance (TA),” in *Universal Personal Communications, 1998. ICUPC’98. IEEE 1998 International Conference on*, vol. 2. IEEE, 1998, pp. 1367–1372.
- [41] C. Gentile, N. Alsindi, R. Raulefs, and C. Teolis, “Ranging and localization in harsh multipath environments,” in *Geolocation Techniques*. Springer, 2013, pp. 17–57.
- [42] N. A. Alsindi, B. Alavi, and K. Pahlavan, “Measurement and modeling of ultrawideband TOA-based ranging in indoor multipath environments,” *IEEE Transactions on Vehicular Technology*, vol. 58, no. 3, pp. 1046–1058, 2009.
- [43] “Errors in automatic location identification using timing advance, author=Yost, George P and Panchapakesan, S,” in *Vehicular Technology Conference, 1998. VTC 98. 48th IEEE*, vol. 3. IEEE, 1998, pp. 1955–1958.