

Engine Compartment and Beneath the Chassis UWB Channel
Model for Intra-Vehicular Wireless Sensor Networks

by

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This is to certify that I have examined this copy of a master's thesis by

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ABSTRACT

Intra-vehicular wireless sensor networks (IVWSN) is a cutting edge research topic that brings cost reduction, assembly and maintenance efficiency by the removal of the wiring harnesses within the vehicle and enables integration of new sensors into the vehicle locations where cable connection is not possible. Providing energy efficiency through the low duty cycle operation and high reliability by exploiting the large bandwidth, Ultra-wideband (UWB) has been determined to be the most appropriate technology for IVWSN. This thesis consists of two UWB channel models for IVWSN within the engine compartment and beneath the chassis. The engine compartment channel model aims to model the average behavior of the channel based on the measurements of 19×19 links for different types and conditions of the vehicle. The model is based on the derivation of the path loss exponent, the power variation around the path loss exponent, the parameters of the modified Saleh-Valenzuela (SV) model, the variations of the observed power delay profiles (PDP) around the SV model. The proposed model has been validated by comparing the received energy and root mean square delay spread of the generated and observed PDPs. The beneath the chassis channel model aims to model the time variation of the channel based on the data collected under different scenarios including different road types and vehicle speed. The model is based on applying time-series analysis, specifically ARIMA model, on the parameters of the modified SV model. The proposed model has been validated by analyzing the distribution of the residuals between generated and experimental data.

ÖZETÇE

Araç içi kablosuz algılayıcı ağları araç içinde kablolu iletişim sistemlerinin kaldırılmasıyla iletişim masraflarını azaltan, bakım, montaj kolaylığı sağlayan son teknoloji bir araştırma konusudur. Ayrıca araç içi kabloların kaldırılmasıyla açılan yeni yerlere algılayıcı yerleştirilmesini ve kabloyla iletişimin sağlanamadığı yerlerde iletişimin gerçekleşmesini sağlar. Ultra geniş bant düşük görev döngüsü operasyonu sayesinde enerji verimliliği sağlaması, geniş bant aralığından faydalanması bakımından araç içi kablosuz algılayıcı ağları için en iyi teknoloji olarak ön plana çıkmaktadır. Bu tez araç içi kablosuz algılayıcı ağları için motor içi ve şase altı olmak üzere iki adet ultra geniş bant kanal modeli içermektedir. Motor içi kanal modeli, kanalın ortalama davranışını 19×19 'luk hatlardaki ölçüleri kullanarak farklı araçlar ve durumlar için modellemeyi hedeflemektedir. Bu model, yol kaybı üstü, yol kaybı üstü etrafındaki güç değişimi, biraz değiştirilmiş Saleh-Valenzuela (SV) model parametreleri ve elde edilen güç gecikme profilinin SV modeli etrafındaki değişimlerine dayanmaktadır. Önerdiğimiz bu model, alınan enerji ve etkin değer gecikme yayılımının gerçek değerlerinin model tarafından üretilmiş değerleriyle karşılaştırılmasıyla doğrulanmıştır. Şase altı kanal modeli kanalın zaman değişimlerinin farklı yol çeşitleri ve hızlar gibi değişik senaryolar altında nasıl davrandığını modellemeyi hedeflemektedir. Bu model biraz değiştirilmiş SV modeli parametrelerinin zaman serisi analizine dayanmaktadır. Burada kullandığımız zaman serisi metodu tümleşik özbağlanımlı yürüyen ortalamadır (ARIMA). Önerilen bu model gerçek veri ile modellenmiş veri arasındaki farkların dağılımının analiziyle geçerli kılınmıştır.

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Chapter 1

INTRODUCTION

1.1 IVWSN

The proliferation of the electronic systems within the vehicle as they are replacing mechanical or hydraulic counterparts led to an increase in the number of sensors monitoring various quantities for them to improve their performance [1]. Since every sensor needs to be wired to an electronic control unit (ECU) to communicate the sensor information and to the battery of the vehicle to supply power, part cost, maintenance and assembly problems arise within the vehicle. Removing the wiring not only provides cost reduction but also fuel efficiency due to the decrease of the vehicle weight. Moreover, such wireless technology allows the integration of new sensors into the vehicle locations where cable connection is not possible [2]. The first adoption of wireless sensor networks within the vehicle is expected to be through these new sensor technologies and non-critical vehicle applications either requiring a lot of wiring such as park sensors or not operating efficiently due to wiring such as steering wheel angle sensors. Once the performance and reliability of these applications are proven by extensive tests on the road, the wiring can be removed for more critical applications such as ABS (Anti-lock Braking System) [3].

1.2 UWB

Among alternative communication technologies such as radio-frequency identification (RFID) [4], narrowband [5, 6], spread spectrum [7, 8], UWB has been demonstrated to satisfy the high reliability constraints of IVWSN applications by exploiting the

large bandwidth and their energy efficiency constraints through the low duty cycle operation. UWB is defined as the transmission with the bandwidth more than the lesser of 500 MHz and 20% of the center frequency. This huge bandwidth enables UWB transmission to be resistant against multipath fading and signal power attenuation providing robust communication at low transmission power and high communication rate.

1.3 Related Work

In order to design a well-functioning UWB system, an appropriate channel model should be extracted. The vast literature on UWB channel models developed for indoor [9–13], outdoor [14–17], around the human body [18, 19] or industrial environments [20] cannot be applied for IVWSN since the vehicle is very different from these environments containing a large number of metal reflectors at short distance with a lot of vibrations resulting in dense multipath. The UWB channel models developed for different parts of the vehicle, including engine compartment [21, 22], beneath the chassis [21, 22], passenger compartment [23–26] and trunk [27], on the other hand are extracted based on the measurements in a limited number of locations, 24 locations at maximum, without building a detailed simulation model and testing the robustness of the model under different scenarios such as different types and conditions of vehicles. Only recently such a detailed model has been proposed and tested beneath the chassis of the vehicle [28, 29]. In addition, previous studies aim to represent the average behavior and the variations around the average behavior of the UWB channel without adopting time-series analysis. Even when these works collect data on the vehicle moving on the road, they still consider the distribution of the power delay profiles (PDP) around their average value without considering the ordering of the data in time. Such modeling therefore does not allow the generation of the successive PDPs. Time-series analysis on the other hand models the data as an ordered sequence of values. Embedding this ordering in the model allows the representation of the temporal variations in the channel.

1.4 Contributions

This thesis consists of two parts, which each one has a distinct UWB channel model. The goal of the first channel model is to propose a robust UWB channel model within the engine compartment of the vehicle though the collection of data at 19×19 locations for two types of vehicles under different scenarios. The engine compartment channel measurement campaigns in [21] and [22] are performed at only 5 and 9 locations respectively decreasing the reliability of the measurement results. Moreover, they do not propose a simulation model for the UWB engine compartment channel but only derive a subset of the required channel model parameters. The original contributions of the first model are as follows:

- We derive the distributions, parameters and dependence relations related to the UWB engine compartment channel model including the path loss and power variation around the expected path loss; the distribution of the cluster inter-arrival times and the dependence of the cluster amplitude and cluster decay rate on the cluster arrival times in the SV model; and the probabilistic distribution of the variation of the observed PDPs around the SV model. This is the first work to provide a complete analysis of the distributions, parameters and dependence relations related to the UWB engine compartment channel model.
- We generate the simulation model for the UWB channel within the engine compartment and validate the model by comparing the received energy and root mean square delay spread obtained from the simulation and experimental data. This is the first simulation model generated for the UWB engine compartment channel.
- We analyze the validity of the simulation model and the sensitivity of the model parameters for different vehicle types and conditions. This is the first work to analyze the validity of the engine channel model across a wide range of scenarios.

The goal of the second channel model is to provide the time-variation model for the UWB channel beneath the chassis of a vehicle by employing time-series analysis on the data collected at different vehicle speeds on different road types. Previous work on the modeling of the temporal variations in the UWB channel mostly focus on the representation of the non-stationary attenuation due to obstructing people [30–33] and movement of a receiver along a linear trajectory at a constant velocity [34] in indoor environment. The time variations beneath the chassis have been demonstrated to have stationary distribution so the models describing non-stationary attenuation due to obstructing people cannot be applied. Only [31, 35] also model small-scale signal variations due to scattered propagation paths in indoor environment but again by only focusing on the distribution of the variations around the average PDP without considering their ordering in time. The original contributions of the second model are as follows:

- We employ auto-regressive integrated moving average (ARIMA) model to determine the time evolution of the parameters of the modified Saleh-Valenzuela (SV) model derived for the beneath the chassis UWB channel [29]. ARIMA model is a flexible tool that provides a good understanding of trends, correlation and forecasting in time series. The modified SV model aims to generate the clustering phenomenon in the PDP by determining the distribution of the inter-arrival times of the clusters, the cluster amplitude and ray amplitude decay function. The ARIMA model is used to determine the variation in the cluster arrival times, cluster amplitude and ray amplitude decay rate. This is the first work to provide a time-varying UWB channel based on the time-series analysis allowing the regeneration of successive PDPs.
- We validate the proposed ARIMA model on the SV model parameters as a time-varying UWB channel model beneath the chassis of the vehicle based on the analysis of the residuals between generated and observed values and the sensitivity of the model parameters for different vehicle speeds and road types.

This is the first work to analyze the validity of the time varying model across a wide range of scenarios.

1.5 Organization

The organization of this thesis as follows: In Chapter 2 we present engine compartment UWB channel model. Chapter 3 discusses the beneath the chassis UWB channel model. Finally, Chapter 4 includes the conclusion and future direction of this study.

Chapter 2

ENGINE COMPARTMENT UWB CHANNEL MODEL

2.1 Experimental Setup

The channel measurement data are collected by using Agilent 8719ES Vector Network Analyzer (VNA) covering the frequency range [3.1, 10.6] GHz using 1601 points. The UWB antennas used in the experiments are omnidirectional and directed towards the bottom of the vehicle. The antennas are connected to the VNA via low-loss coaxial cables. The VNA is calibrated for each frequency band to eliminate the effect of signal distortions by the cables. The coaxial cable may influence the parameters of the UWB antennas due to their small size. However, we observed that the measurements of the VNA remain stable upon the movement of the cables demonstrating that they do not radiate enough energy to alter our results. The return loss at the antennas has been measured to be negligible across the band of interest.

We performed our channel measurement in Fiat Linea and Peugeot Bipper between every pair of the sensor locations shown in Figures 2.1 and 2.2 respectively for two scenarios where the engine is off and on. The sensor locations are chosen to cover the whole area within the engine compartment.

VNA provides the complex transfer function $H(f)$. We process this transfer function to obtain a reliable PDP in MATLAB as follows:

- $H(f)$ is passed through the Hamming window to decrease the side lobes then the Inverse Fourier Transform (IFFT) to generate the impulse response $h(t)$ at the output. The PDP is then computed as $|h(t)|^2$ normalized with respect to the reference PDP measured between a transmitter-receiver pair at reference distance.

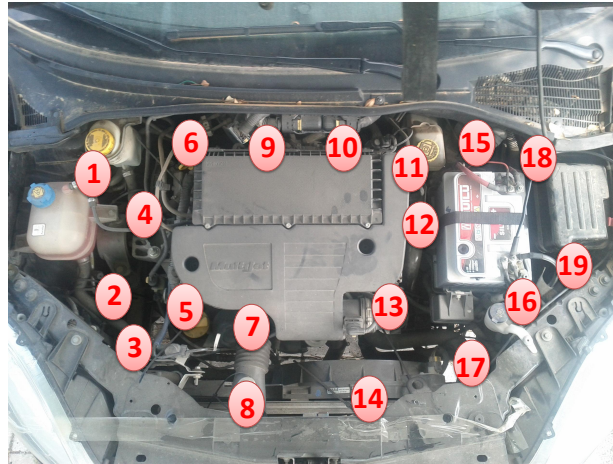


Figure 2.1: Sensor locations within the engine of Fiat Linea

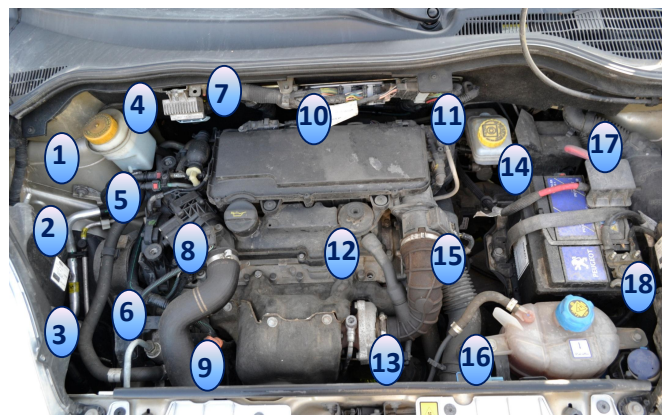


Figure 2.2: Sensor locations within the engine of Peugeot Bipper

- The PDP is shifted by the corresponding propagation delay to the left to guarantee that the first bin is aligned with the first multipath component.
- The delay axis of the PDP is quantized into bins. The received power is integrated within each bin. The bin width is chosen to contain 5 samples to make a good compromise between high delay resolution and noise reduction.

The goal of this model is to derive and validate the simulation model for the resulting PDP.

2.2 Path Loss and Power Variation

The path loss between a transmitter-receiver pair originates from both the free space attenuation and the level of absorption, reflection, diffraction, and refraction in the engine compartment. The path loss model is given as

$$PL_{[\text{dB}]}(d) = PL_{[\text{dB}]}(d_r) + 10n\log_{10}\left(\frac{d}{d_r}\right) + N \quad (2.1)$$

where $PL_{[\text{dB}]}(d)$ and $PL_{[\text{dB}]}(d_r)$ are the path loss at distance d and reference distance $d_r = 7$ cm in decibels respectively, n is the path loss exponent and N is a zero-mean Normal random variable with standard deviation σ_N [36].

Figure 2.3 shows the path loss as a function of the distance along with the best linear fit obeying Equation (2.1) for the engine compartment of Fiat Linea when the engine is off. The path loss exponent n is found to be 3.5.

Figure 2.4 shows the cumulative distribution function (cdf) of the experimental power variation in decibels along with the least square fit of the cdf of the normal random variable for the engine compartment of Fiat Linea when the engine is off. The power variation is calculated by finding the difference between the measured path loss values and the best linear fit in Figure 2.3, and represented by N in Equation (2.1). We observe that the frequently used normal random variable is an appropriate model for the engine compartment with standard deviation $\sigma_N = 6.3$ dB.

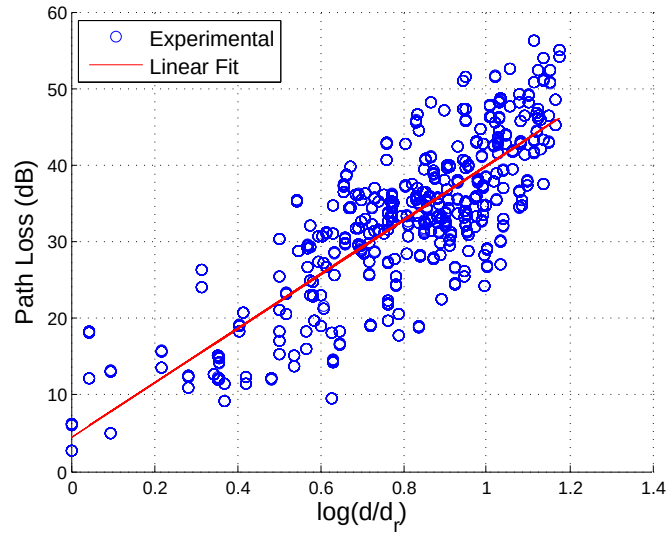


Figure 2.3: Dependence of the path loss on the distance within the engine compartment of Fiat Linea when the engine is off.

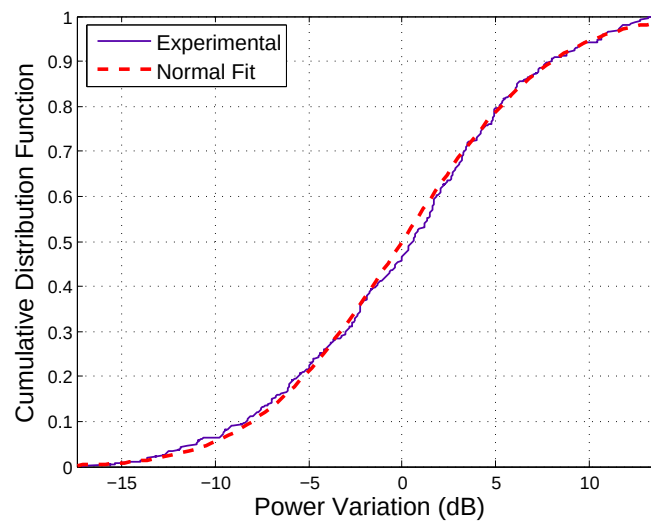


Figure 2.4: Cumulative distribution function of the power variation

Table 2.1: Parameters of the path loss and power variation. The unit of $PL_{[\text{dB}]}(d_r)$ and σ_N are dB.

Scenario	n	$PL_{[\text{dB}]}(d_r)$	σ_N
Linea off	3.5369	4.436	6.25
Linea on	3.5594	4.194	6.24
Bipper off ₁	2.8090	10.63	5.31
Bipper off ₂	3.563	4.436	5.58

Table 2.1 shows the parameters of the path loss and power variation for three scenarios: “Linea off” represents Fiat Linea with engine off, “Linea on” corresponds to Fiat Linea with engine on, “Bipper off” is for Peugeot Bipper with engine off. The subscript 1 corresponds to the case where the values of n , $PL_{[\text{dB}]}(d_r)$ and σ_N are obtained by the curve fitting of the measured data to Equation (2.1) in a minimum mean square error sense whereas the subscript 2 corresponds to the case where the same $PL_{[\text{dB}]}(d_r)$ value as that of the “Linea off” is used, and n and σ_N values are obtained by the curve fitting of the measured data to Equation (2.1) in a minimum mean square error sense. The reason for using the latter estimation method is the expectation that the path loss at the reference distance would not be so different for different engines. As also observed in Figure 2.5, this method does not increase the standard deviation σ_N significantly and allows us to obtain a more generic path loss model with similar estimated n , $PL_{[\text{dB}]}(d_r)$ and σ_N values for different types of vehicles. We can therefore conclude that turning the engine on and the type of the vehicle do not affect the path loss parameters significantly.

In [22], the authors have stated that the estimated path loss parameters are $n = 1.51$, $PL_{[\text{dB}]}(d_r) = 6.32$ dB and $\sigma_N = 3$ dB based on the data collected from 9 measurement pairs in the engine compartment of the GM Escalade but the corresponding values change to $n = 4.73$, $PL_{[\text{dB}]}(d_r) = 35.15$ dB and $\sigma_N = 1.06$ dB if the measurement from two positions are excluded, which decreases the reliability of the estimated values. Our estimated values are robust to the exclusion of a few measurement points due to the collection of a large amount of data within the engine.

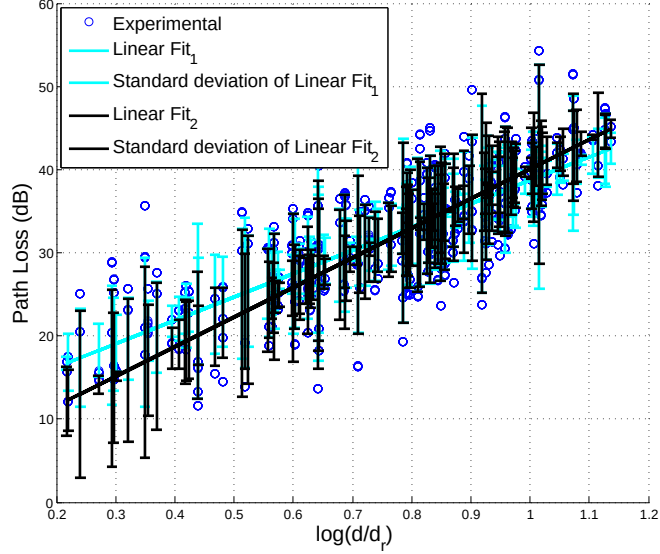


Figure 2.5: Dependence of the path loss on the distance within the engine compartment of Peugeot Bipper when the engine is off.

2.3 Impulse Response Analysis

The PDP in the engine compartment consists of many clusters as illustrated in Figure 2.6. The PDP in this figure belongs to the receiver at location 1 and transmitter at location 4 in the engine compartment of Fiat Linea shown in Figure 2.1. We determined the arrival time of each cluster by using the automatic clustering algorithm presented in [37] then validated the accuracy of the algorithm by visual inspection. Assuming that the slope changes at the beginning of each cluster, the automatic clustering algorithm identifies the change points of the partial slopes of the impulse response.

The arrival time and amplitude of the clusters in the PDP is modeled by using a modified SV model [9], which is frequently used to represent the behavior of the random clusters in UWB channels. The SV model defines the impulse response of a system as

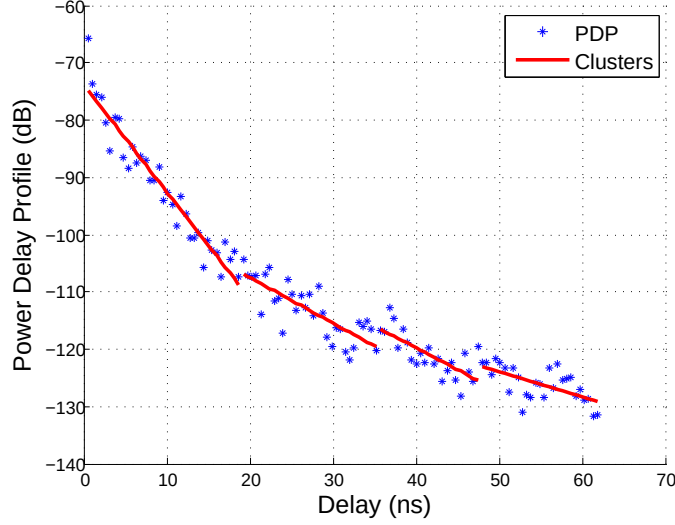


Figure 2.6: Typical PDP in the engine compartment (receiver 1 and transmitter 4 in the engine compartment of Fiat Linea shown in Figure 2.1)

$$y(t) = \sum_{b=0}^B \sum_{a=0}^A \alpha_{b,a} e^{j\phi_{b,a}} \sigma(t - T_b - \tau_{b,a}) \quad (2.2)$$

where $\alpha_{b,a}$ is the gain and $\phi_{b,a}$ is the phase of the a -th component in the b -th cluster, T_b is the delay of the b -th cluster, $\tau_{b,a}$ is the delay of the a -th multipath component in the b -th cluster relative to the b -th cluster arrival time T_b , B is the number of clusters and A is the number of the multipath components within a cluster. The phases $\phi_{b,a}$ are uniformly distributed in the range $[0, 2\pi]$.

In the classical SV model, the distributions of the cluster arrival times are given by a Poisson process so that the inter-cluster arrival times are exponentially distributed. This model also uses a Poisson process for the ray arrival times within each cluster. Moreover, both the amplitude of the clusters and the amplitude of the rays within each cluster are decreasing exponentially with the arrival time. The decay rate of the clusters and rays are different but fixed independent of their arrival time. We will now analyze the distribution of the inter-cluster arrival times, the dependence of the amplitude of the clusters and the decay rate of the rays within each cluster on the

arrival times of the clusters for the UWB channel within the engine compartment of the vehicle. Since each delay bin contains significant amount of energy due to the dense arrival of the multi-path components in the engine compartment, we don't analyze the distributions of the ray arrivals within each cluster but assume a realization of the impulse response based on a tapped delay line model with regular tap spacings.

2.3.1 Inter-arrival Times of Clusters

Figure 2.7 shows the cdf of the inter-arrival times of the clusters for the engine compartment of Fiat Linea when the engine is off. We observed that the Weibull distribution matches better with the experimental cdf than the exponential distribution used in the classical SV model because of the nonrandom local configuration of the engine compartment [19]. Kolmogorov-Smirnov (KS) test results with a 95%-confidence interval for Weibull and exponential distributions are 0.0238 and 0.2338 respectively justifying this observation (KS-Test is a nonparametric test determining the goodness of a reference distribution for the experimental data). The Weibull distribution is given as

$$f(x) = \begin{cases} \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k} & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (2.3)$$

where $k > 0$ is the shape parameter and $\lambda > 0$ is the scale parameter of the distribution. The shape and scale parameters of the Weibull distribution are found to be $k = 2.06$ and $\lambda = 20.79$ ns respectively.

Table 2.2 shows the shape and scale parameters of the Weibull fit for the inter-arrival times of the clusters, and KS-test result with a 95%-confidence interval for Weibull and exponential distributions with the experimental inter-arrival times of the clusters for three scenarios as described in detail for Table 2.1. KS-test results justify that the Weibull distribution is a better fit than the exponential distribution for different types and conditions of the vehicle. Moreover, the shape and scale parameters of the Weibull fit for the inter-arrival times of the clusters do not vary significantly when the engine of the vehicle is turned on or the vehicle type is different: The KS

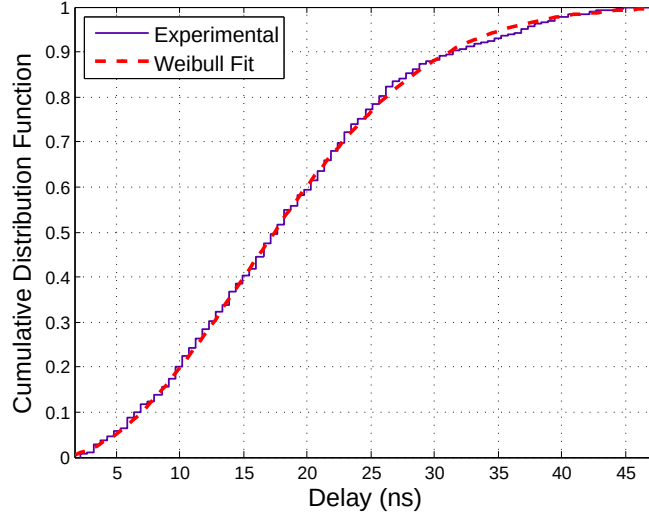


Figure 2.7: Cumulative distribution function of the inter-arrival times of the clusters.

statistic for the Weibull fit of “Linea off” and “Linea on” cases is 0.1957 whereas that for the Weibull fit of “Linea off” and “Bipper off” cases is 0.063 (KS-statistic for two empirical distribution functions F_1 and F_2 is defined as $\sup_x |F_1(x) - F_2(x)|$).

The previous work on the engine compartment UWB channel model does not analyze the suitability of alternative distributions for the inter-arrival times of the clusters but it is clear that exponential distribution does not fit well their experimental data either [21, 22]. On the other hand, [28, 29] similarly observe that Weibull fit is a better fit for the inter-arrival times of the clusters beneath the chassis. The scale parameter λ beneath the chassis is less than that of the engine compartment, less than 15 ns for the same scenarios, and the shape parameter k beneath the chassis is similar to that of the engine compartment but with much larger variation from 1.9 to 2.8 for the same scenarios.

2.3.2 Cluster Amplitude Decay Function

Figure 2.8 shows the dependence of the cluster amplitude on the cluster arrival time for the engine compartment of Fiat Linea when the engine is off. The cluster amplitude

Table 2.2: Shape and scale parameters of the Weibull fit for the inter-arrival times of the clusters, and KS-test result with a 95%-confidence interval for Weibull and exponential distributions with the experimental inter-arrival times of the clusters denoted by KS_W and KS_E respectively. The unit of λ is ns.

Scenario	k	λ	KS_W	KS_E
Linea off	2.06	20.7879	0.0238	0.2338
Linea on	2.622	24.4654	0.0484	0.294
Bipper off	2.292	21.3313	0.0541	0.2687

Scenario	c_{11}	c_{10}	c_{21}	c_{20}	τ_{bc}
Linea off	-1.143	-7.5	-0.619	-21.45	26.6
Linea on	-1.256	-7.38	-0.645	-20.15	25
Bipper off	-1.223	-6.728	-0.633	-18.67	28

Table 2.3: Parameters of the cluster amplitude decay function. The unit of c_{11} and c_{21} is dB/ns. The unit of c_{10} and c_{20} is dB. The unit of τ_{bc} is ns.

denotes the power of the first bin of the cluster relative to the total energy. The reason for normalizing the cluster amplitudes by the total energy is to eliminate the dependence on the distance. The cluster amplitude decay function is modeled by using the dual slope linear model as

$$f(T_b) = \begin{cases} c_{11} \cdot T_b + c_{10}, & T_b \leq \tau_{bc} \\ c_{21} \cdot T_b + c_{20}, & T_b > \tau_{bc} \end{cases} \quad (2.4)$$

where $f(T_b)$ represents the power of the first bin of the cluster arriving at delay T_b relative to the total energy in decibels, τ_{bc} is the breakpoint between the two lines, c_{11} and c_{21} are the slopes of the least square fit line before and after the breakpoint respectively, c_{10} and c_{20} are the cluster amplitude axis intercept point of the least square fit line before and after the breakpoint respectively. The parameters of the model are estimated as follows: $c_{11} = -1.143$ dB/ns, $c_{10} = -7.5$ dB, $c_{21} = -0.619$ dB/ns, $c_{20} = -21.45$ dB, $\tau_{bc} = 26.6$ ns.

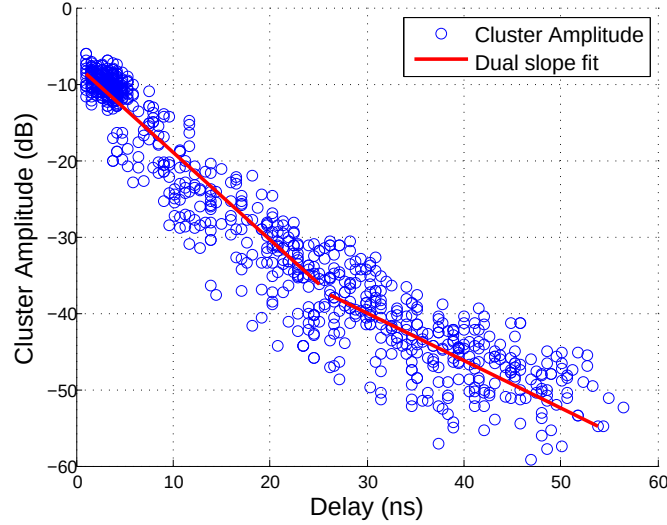


Figure 2.8: Dependence of the cluster amplitude on the cluster arrival time.

Table 2.3 shows the parameters of the cluster amplitude decay function for three scenarios as described in detail for Table 2.1. We observe that these parameters do not change significantly for different types and conditions of the vehicle. The previous work on the engine compartment UWB channel model provide a linear fit for the cluster amplitude decay function with much slower decay, slope -0.323 dB/ns, based on the data collected from at most 9 measurement points [21, 22]. On the other hand, [28, 29] similarly observe a dual slope linear model for the cluster amplitude decay function beneath the chassis. Although the slope of the first line is comparable for both the engine compartment and beneath the chassis, the slope of the second line is slightly higher for the engine than beneath the chassis due to the large number of obstructing elements densely deployed within the engine compartment at short distance.

2.3.3 Ray Amplitude Decay Function

Once the power of the first bin of all the clusters is determined by calculating the cluster amplitude given in Equation (2.4), the ray decay rate of these clusters need to be specified so that we can calculate the power of all the bins within these clusters.

Scenario	d_{11}	d_{10}	d_{21}	d_{20}	τ_{br}
Linea off	-0.057	9.381	-0.01	9.121	5.56
Linea on	-0.05	9.323	-0.013	9.108	5.86
Bipper off	-0.054	9.306	-0.008	8.98	5.33

Table 2.4: Parameters of the ray amplitude decay function. The unit of d_{11} and d_{21} is dB/ns². The unit of d_{10} and d_{20} is dB/ns. The unit of τ_{br} is ns.

Assuming that the decay in each cluster is linear as illustrated in Figure 2.6, the power of the a -th bin of the b -th cluster is formulated as

$$g(T_b + \tau_{b,a}) = f(T_b) - \xi(T_b)\tau_{b,a} \quad (2.5)$$

where $g(T_b + \tau_{b,a})$ is the power of the a -th bin of the b -th cluster arriving at delay T_b relative to the total energy in decibels and $\xi(T_b)$ is the decay rate of the cluster arriving at delay T_b in decibels.

Figure 2.9 shows the dependence of the ray amplitude decay function ξ on the cluster arrival time T_b for the engine compartment of Fiat Linea when the engine is off. The ray amplitude decay function is modeled by using the dual slope linear model as

$$\xi(T_b) = \begin{cases} d_{11} \cdot T_b + d_{10}, & T_b \leq \tau_{br} \\ d_{21} \cdot T_b + d_{20}, & T_b > \tau_{br} \end{cases} \quad (2.6)$$

where τ_{br} is the breakpoint between the two lines, d_{11} and d_{21} are the slopes of the least square fit line before and after the breakpoint respectively, d_{10} and d_{20} are the ray decay rate axis intercept point of the least square fit line before and after the breakpoint respectively. The parameters of the model are estimated as follows: $d_{11} = -0.057$ dB/ns², $d_{10} = 9.381$ dB/ns, $d_{21} = -0.01$ dB/ns², $d_{20} = 9.121$ dB/ns, $\tau_{br} = 5.56$ ns.

Table 2.4 shows the parameters of the ray amplitude decay function for three scenarios as described in detail for Table 2.1. Similar to the cluster amplitude decay

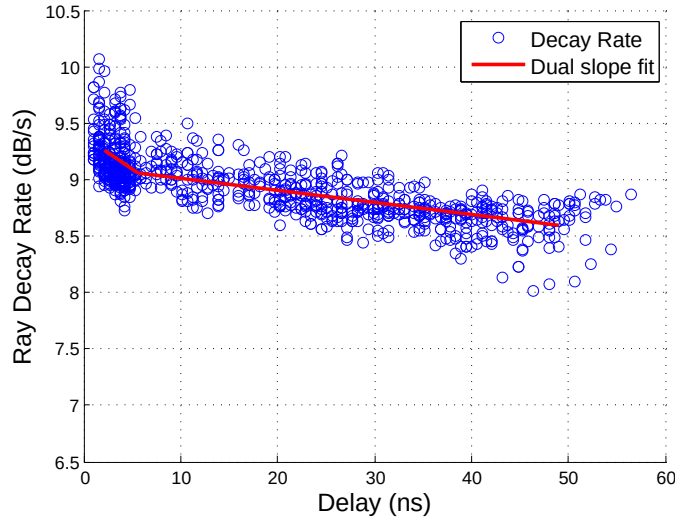


Figure 2.9: Dependence of the ray decay rate on the cluster arrival time.

function, we observe that the parameters of the ray amplitude decay function do not vary significantly for different vehicle types and conditions. The previous work on the engine compartment UWB channel model do not provide the dependence of the ray amplitude decay on the cluster arrival times [21, 22]. On the other hand, [28, 29] similarly observe a dual slope linear model for the ray amplitude decay function beneath the chassis. However, the breakpoint of the dual slope linear model beneath the chassis is around 27 ns, which is much larger than that of the engine compartment.

We have also investigated whether the power-law fit provides better results than the exponential fit given in Equation (2.6). Although some of the studies on the UWB channel model for the environments containing a large number of metallic reflectors [14, 20] report that the ray decay follows a power-law fit rather than an exponential fit, the MSE (mean-square error) of the power law fit is either greater or very close to that of the exponential fit in the engine compartment, i.e. the MSEs of the exponential fit are 0.0334, 0.0296 and 0.0328 whereas the MSEs of the power-law fit are 0.0326, 0.0300 and 0.0319 in unit of $(\text{dB/ns})^2$ for “Linea off”, “Linea on” and “Bipper off” cases respectively. This validates the exponential fit dual slope linear

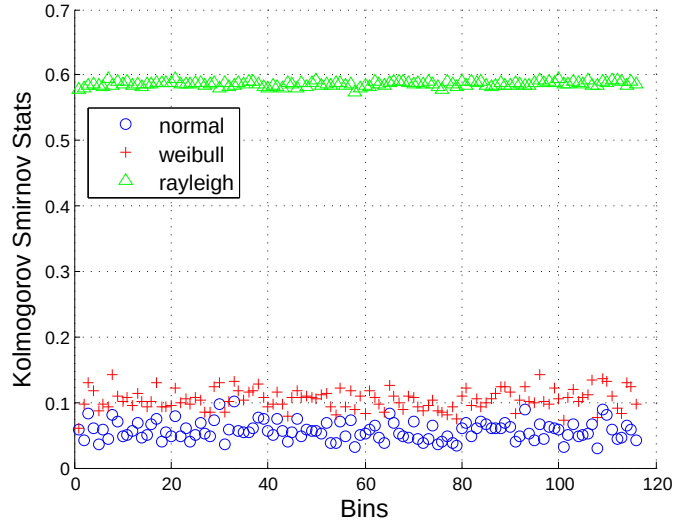


Figure 2.10: Results of the KS test with a 95%-confidence interval for the difference between the observed PDPs and the SV model in each delay bin.

model given in Equation (2.6).

2.4 Variation of PDP Around SV Model

The SV model is used to build the clustered impulse response as shown with the use of lines in Figure 2.6. However, the actual impulse response varies around this SV model. To understand the distribution of these variations, we analyzed the best fit for these variations in each delay bin.

Figure 2.10 shows the results of the KS test with a 95%-confidence interval for Normal, Weibull and Rayleigh distributions for the engine compartment of Fiat Linea when the engine is off. We observe that normal distribution is the best distribution in almost all the delay bins. Figure 2.11 shows the mean and standard deviation of the best fit normal distribution in all the delay bins. We observe that the mean and standard deviation is independent of the delay with average values $\mu_z = 0$ dB and $\sigma_z = 3.03$ dB respectively. The average of the mean value 0 demonstrates that the SV model correctly represents the measured PDPs.

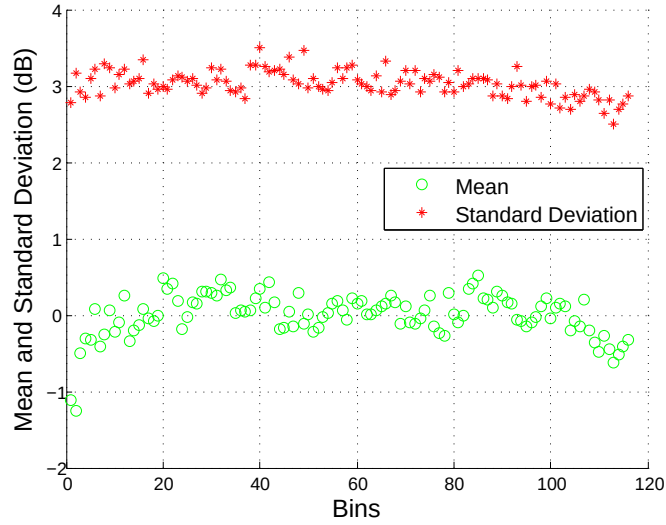


Figure 2.11: Mean and standard deviation of the difference between the observed PDPs and the SV model in each delay bin.

We observed similar behavior in the variation of the PDPs around the SV model when the engine of Fiat Linea is turned on and for Peugeot Bipper. Table 2.5 shows the average standard deviation of the variation of the PDP around SV model for three scenarios as described in detail for Table 2.1. We observe that the average standard deviation of the variation of the PDP around the SV model is independent of not only the delay bin but also the type and condition of the vehicle.

Table 2.5: Average standard deviation of the variation of the PDP around the SV model. The unit of σ_z is dB.

Scenario	σ_z
Linea off	3.03
Linea on	3.02
Bipper off	3.13

2.5 Simulation Model

2.5.1 Generation of Simulation Model

<i>Input:</i> Distance between transmitter and receiver
<i>Output:</i> Power delay profile between transmitter and receiver
<pre> 1: begin 2: $T_0 = d/c, B = 0;$ 3: while $T_B \leq \text{Delay spread}$ 4: $T_{B+1} = T_B + \text{weibull}(\lambda, k);$ 5: $B = B + 1;$ 6: end 7: Calculate the cluster amplitudes by using dual slope linear model $f(T_b - T_0)$ for $b = 0 : (B - 1)$ 8: Calculate the ray amplitudes within the clusters by using the function $g(T_b - T_0 + \tau_{b,a}) = f(T_b - T_0) -$ $\xi(T_b - T_0)\tau_{b,a}$ for $b = 0 : (B - 1)$ and $\tau_{b,a} \in [0, T_{b+1} - T_b]$ 9: Scale the PDP according to the path loss function 10: Add Gaussian random variable $N(0, \sigma_z^2)$ to each delay bin of PDP 11: end </pre>

Figure 2.12: Algorithm for generating the simulation model for the engine compartment UWB channel.

We now describe the algorithm for generating the simulation model for the engine compartment UWB channel based on our findings in Sections 2.2, 2.3 and 2.4. The algorithm is given in Figure 2.12 with the details as explained next:

- The cluster arrival times are calculated first based on our findings in Section 2.3.1. The arrival time of the first cluster is at the propagation delay $T_0 = d/c$, where d is the distance between the transmitter and receiver, and c is the speed of light. The arrival time of the following clusters are calculated by computing the random value from the Weibull distribution with the parameters provided in Table 2.2 and adding to the previous arrival time. This continues as long as the computed arrival times are less than the maximum delay spread.
- The power of the first bin of the cluster relative to the total energy, cluster amplitude, corresponding to the arrival time of each cluster is computed next

based on our findings in Section 2.3.2. Since the derivation of the cluster amplitude decay function assumes that the PDP is shifted to the left by the propagation delay, the cluster amplitude is calculated by using the dual slope linear model given in Equation (2.4) evaluated at $T_b - T_0$ for $b = 0 : (B - 1)$ with the parameters provided in Table 2.3.

- The power of the following bins of the cluster are computed based on our findings in Section 2.3.3. The power of the a -th bin of the b -th cluster is calculated by using the Equation $g(T_b - T_0 + \tau_{b,a}) = f(T_b - T_0) - \xi(T_b - T_0)\tau_{b,a}$ where $\xi(T_b - T_0)$ is the ray amplitude decay function modeled by using the dual slope linear model formulated in Equation (2.6) with the parameters given in Table 2.4.
- Since up to now, the goal was to identify the general shape of the impulse response, the power of all the bins are derived based on the normalized PDPs. The next step in generating the simulation model is to scale the PDP by using the path loss model provided in Equation (2.1) with the parameters summarized in Table 2.1 as derived in Section 2.2.
- The random variations of the observed PDP around the SV model are added to each delay bin based on our findings in Section 2.4. The final PDP is calculated by adding independent normal random variables with the parameters summarized in Table 2.5 to each delay bin of the PDP.

2.5.2 Validation of Simulation Model

We implemented the simulation model described in Section 2.5.1 in Matlab for all three scenarios including Fiat Linea with engine off, Fiat Linea with engine on and Peugeot Bipper with engine off, and validated the model by comparing the resulting cdf of the receive energy and root mean square (rms) delay spread of the simulated and experimental PDPs.

Figure 2.13 shows the cdf of the received energy of the experimental and simulated

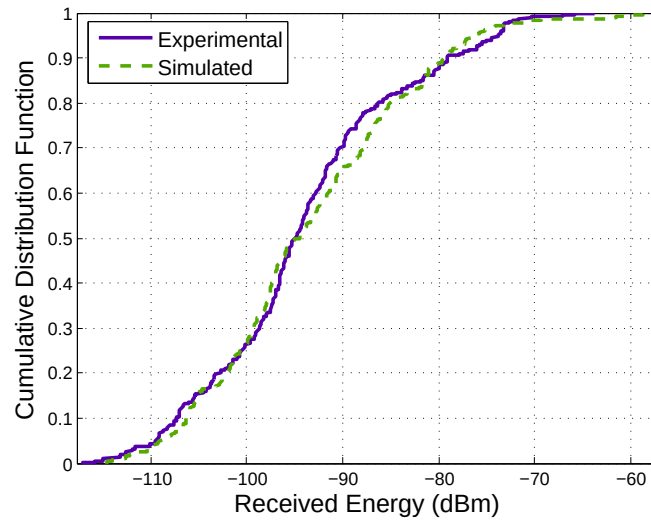


Figure 2.13: Cumulative distribution function of the received energy of the experimental and simulated PDPs.

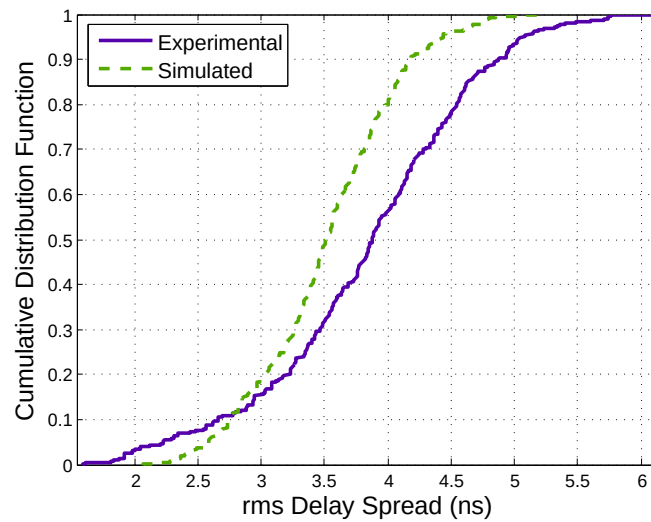


Figure 2.14: Cumulative distribution function of the rms delay spread of the experimental and simulated PDPs.

PDPs for the engine compartment of Fiat Linea when the engine is off. We observe that the experimental and simulated PDPs are in good agreement in terms of received energy with KS statistic equal to 0.0877. We observe similar agreement for Fiat Linea with engine on and Peugeot Bipper with engine off scenarios with KS statistic equal to 0.0936 and 0.0523 respectively.

Figure 2.14 shows the cdf of the rms delay spread of the experimental and simulated PDPs for the engine compartment of Fiat Linea when the engine is off. The rms delay spread of the simulated PDPs is a little narrower than that of the experimental PDPs with KS statistic equal to 0.2661. This is probably because of the approximation of the cluster amplitude and ray amplitude decay functions by dual slope linear models despite the large variations around this model. We observe similar behavior for Fiat Linea with engine on and Peugeot Bipper with engine off scenarios with KS statistic equal to 0.2398 and 0.0817 respectively.

Chapter 3

BENEATH THE CHASSIS UWB CHANNEL MODEL

3.1 Experiment Setup and Data Processing

The data measurements are conducted in the time domain by using Picosecond Pulse Labs 3500D impulse generator and Agilent DSO91304 Infiniium high performance oscilloscope. The impulse generator is used to periodically generate an ultra short pulse with width of 75 ps. The repetition rate is set to 1 MHz. The oscilloscope is then used to record the received signal. The segmented memory feature of the digital oscilloscope is used to increase the number of pulses that can be captured with the limited memory: The oscilloscope stores information only during the active periods so that the memory is not used during the inactive periods. We capture 1024 successive pulses by sampling 200 ns long signal at 40 Gsamples/s for each pulse.

The UWB antennas used are roughly the size of a playing card, display an omnidirectional pattern, and are directed toward the road surface. The transmitter and receiver antennas are placed beneath the chassis of a commercial vehicle Fiat Linea 25 cm apart from each other as seen in Fig. 3.1. The antennas are connected to the impulse generator and oscilloscope via low-loss coaxial cables. The output of the impulse generator is also connected to the trigger input of the oscilloscope via another low-loss cable for synchronization.

The received signal at the oscilloscope corresponding to each transmitted pulse is processed in MATLAB to derive the PDP through averaging and deconvolution, which is then separated into clusters to determine the parameters of the modified SV model in [29].



Figure 3.1: Sensor locations beneath the chassis

3.1.1 Derivation of PDP

The received signal at the oscilloscope corresponding to each transmitted pulse is first clipped from the beginning and end to extract the signal part with significant energy. As an example, Fig. 3.2 shows the received signal for the pulse transmission on the stone road at 20 km/h vehicle velocity. Only the signal part from 35 ns to 60 ns is considered to have significant energy. Following the clipping, the signal is passed through the low pass filter to smooth out the noise. The resulting signal, denoted by $y(t)$, is then processed to eliminate the effect of the cables and antennas. The signal representing the response of the cables and antennas is collected by locating the antennas 2 cm apart in space and denoted by $x(t)$. Assuming that $y(t)$ is the sum of attenuated and delayed copies of $x(t)$, the CLEAN algorithm is used to derive the channel impulse response through deconvolution [38].

In CLEAN algorithm, at the i -th iteration, the correlation of $y(t)$ and $x(t)$ are calculated. The value and delay index of the peak correlation are then recorded as K_i and τ_i respectively. $y(t)$ is then updated by subtracting the effect of the i -th path signal, i.e. $K_i x(t - \tau_i)$, from $y(t)$. This process continues until the energy of the updated $y(t)$ drops under a certain threshold. The value of the threshold is found to be 0.001 by trial and error so that we can obtain a nice PDP. Fig. 3.3 shows the

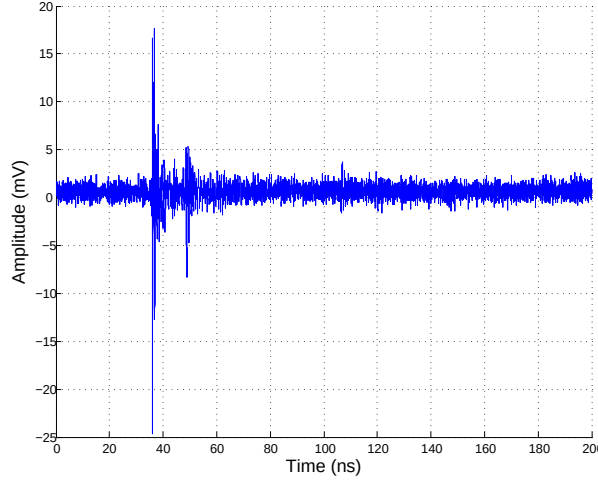


Figure 3.2: Unprocessed raw channel impulse response

deconvolution output of the received signal in Fig. 3.2.

3.1.2 Saleh-Valenzuela Model

In the PDPs recorded beneath the chassis, the multi path signals arrive in the form of clusters. Based on the assumption that the slope changes at the beginning of each cluster, automatic clustering algorithm identifies the change points of the partial slopes of the impulse response [37]. We then validated the accuracy of the algorithm by visual inspection. The clustering is exemplified for the PDP corresponding to the pulse transmission on the stone road at 20 km/h vehicle velocity in Fig. 3.3.

The clustering behavior in the PDPs has been modeled by using the modified SV model in [29]. SV model describes the impulse response as

$$h(t) = \sum_{l=0}^L \sum_{k=0}^K a_{l,k} e^{j\theta_{l,k}} \sigma(t - T_l - \tau_{l,k}) \quad (3.1)$$

where $a_{l,k}$ and $\theta_{l,k}$ are the gain and phase of the k -th component in the l -th cluster respectively, T_l is the delay of the l th cluster, $\tau_{l,k}$ is the delay of the k -th multipath component in the l -th cluster relative to the l -th cluster arrival time T_l , K is the

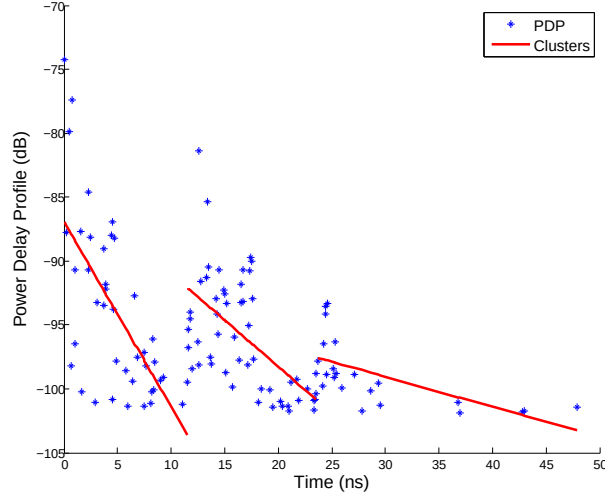


Figure 3.3: PDP corresponding to the pulse transmission on the stone road at 20 km/h vehicle velocity.

number of the multipath components within a cluster and L is the number of clusters. The phases $\theta_{l,k}$ are uniformly distributed in the range $[0, 2\pi]$.

Similar to the PDP in Fig. 3.3, we observed that most of the PDPs beneath the chassis contain 3 clusters. Therefore, the list of the parameters of the SV model that will be used in the time series analysis is as given in Table-3.1.

Table 3.1: List of SV parameters used in time-series analysis

Abbreviation	Scenario
B_1	First break point (ns)
B_2	Second break point (ns)
S_1	First cluster slope (dB/ns)
S_2	Second cluster slope (dB/ns)
S_3	Third cluster slope (dB/ns)
X_1	First break point amplitude (dB)
X_2	Second break point amplitude (dB)

3.2 ARIMA Model

We present the novel idea of modeling the time evolution of the PDPs by representing the changes in their breakpoints, cluster slopes and break point amplitudes with the ARIMA model.

3.2.1 ARIMA Model

ARIMA models are the most general class of models for understanding and forecasting a time series, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied to remove the non-stationarity.

The stationary time series processes can be represented by using autoregressive (AR), moving average (MA) or their combination autoregressive moving average (ARMA) models. In an AR model of order p denoted by AR(p), the value of the process at time t denoted by Z_t is regressed based on its own p past values and a random shock as

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots + \phi_p Z_{t-p} + a_t \quad (3.2)$$

In an MA model of order q , on the other hand, the value Z_t is expressed as a linear combination of a sequence of uncorrelated random variables as

$$Z_t = a_t + \theta_1 a_{t-1} + \theta_2 a_{t-2} + \dots + \theta_q a_{t-q} \quad (3.3)$$

ϕ_i and θ_i represent the i -th AR and MA coefficients respectively whereas a_t is zero mean white Gaussian error term with standard deviation σ_a . MA model is used to represent a stationary process that is purely nondeterministic, i.e. a process contains no deterministic component that can be predicted exactly from its own past, whereas AR model provides the linear dependence of a variable on its own previous values. The combination of these representations helps identifying a time series that might exhibit both phenomenon at certain degrees. Their combination called ARMA process is given as

$$\Phi_p(B)Z_t = \Theta_q(B)a_t \quad (3.4)$$

where $\Phi_p(B)$, and $\Theta_q(B)$ are AR and MA operators with degrees of p and q , respectively, and given as

$$\Phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p \quad (3.5)$$

and

$$\Theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q \quad (3.6)$$

where B and its superscript represent shift operator and the amount of shift to be applied respectively as

$$B^d Z_t = Z_{t-d} \quad (3.7)$$

ARMA model is applicable only for stationary time series. However, many of the real life time series are not stationary. In order to model a non-stationary process using ARMA, the random process needs to be converted into a stationary process. This is usually conducted via differencing of the non-stationary process. When the non-stationary process is reduced to a stationary process ARMA is called auto-regressive integrated moving average (ARIMA) model, which is given as

$$\Phi_p(B)(1 - B)^d Z_t = \theta_0 + \Theta_q(B)a_t \quad (3.8)$$

where p , d , and q are degrees of AR, differencing, and MA operators respectively whereas θ_0 is the deterministic trend term. Thus, ARIMA is the most general class of models flexible to include trends, correlation, and forecasting in time series.

3.2.2 Constructing ARIMA Model

Box-Jenkins procedure is widely used for ARIMA modeling of the time series data [39]. The summary of the procedure is given as a flowchart in Fig. 3.4. For illustration purposes, each step is exemplified with the data of the first cluster slope on asphalt road at the repetition rate of $1MHz$ and vehicle speed of 60 km/h as shown in Fig.

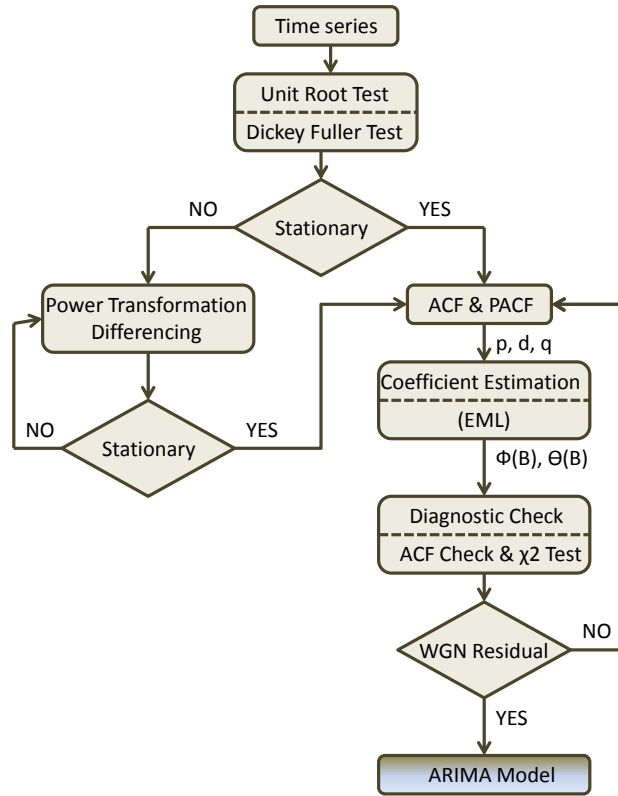


Figure 3.4: Flow chart of overall ARIMA model building

3.6.

3.2.2.1 Decide whether the time-series is stationary

The stationarity of the process is determined by using Dickey Fuller Test. In this test, the existence of a unit root in the AR model corresponds to the non-stationarity of the model. The null hypothesis of Dickey Fuller test is that a unit-root exists. The test provides a p-value, which is used whether to reject or accept the null hypothesis (The p-value is the probability of obtaining a test statistic result at least as extreme or as close to the one that was actually observed, assuming that the null hypothesis is true. A researcher will often reject the null hypothesis when the p-value turns out to be less than a predetermined significance level, often 0.05 or 0.01.)

If the time-series data is stationary, we can skip this step. Otherwise, it must be

reduced to a stationary process. Generally, there are two types of reasons causing non-stationarity in a time-series: non-constant mean and variance. If the mean is not constant, the time series can be reduced to stationary process by applying differencing. The number of differencing operations is denoted by d in the ARIMA model. Although theoretically there is no limit on the number of differencing operations, applying it more than twice is not recommended. On the other hand, if the variance is not constant, then power transformation should be applied to the original data to make the time-series stationary. If the power transformation is needed, it should be performed before differencing.

In the S_1 data shown in Fig. 3.6, we observe that the variance is almost constant but the mean seems to be varying hence we only took difference once skipping power transformation. After the differencing operation, the Dickey Fuller Test yields p-value of 2.215×10^{-19} demonstrating the stationarity of the resulting data.

3.2.2.2 Examine the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)

ACF is the cross-correlation of the process with itself. ACF measures the similarity between the observations as a function of the time lag between them. PACF on the other hand is defined as the correlation between Z_t and Z_{t+k} after the linear dependence of the lags $[t+1, t+k-1]$ is removed. ACF and PACF are used in predicting the orders of the ARIMA model. The AR order p and MA order q are predicted by the visual inspection of PACF and ACF respectively. If PACF or ACF exhibits either exponential or damped sinusoidal behavior, then no order is assigned to p or q , respectively. On the other hand, if either PACF or ACF cuts-off at certain lag, then the cutting lag is assigned as the value of p or q respectively.

The analysis of the ACF and PACF of the S_1 data given in Fig. 3.5 shows that the ACF cuts off after lag 1 but PACF decays exponentially. Thus, the orders might be assigned as $p = 0$ and $q = 1$, whereas $d = 1$ due to differencing, which overall indicates ARIMA(0,1,1) model. However, one should keep in mind that there is no unique

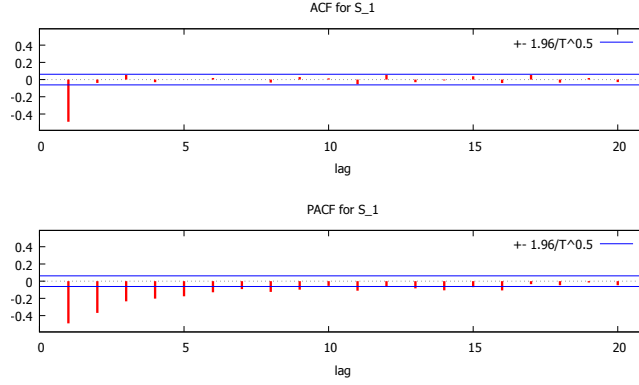


Figure 3.5: ACF and PACF of differenced S_1 data on asphalt road at 1MHz and 60km/h vehicle speed in Fig. 3.6

ARIMA model for a time-series and it is not solely determined by the trends of ACF and PACF. They are just tools, yet very useful, to predict the model orders. Model orders can be changed to find the best model since ARIMA model determination is an iterative process as illustrated in Fig. 3.4.

3.2.2.3 Estimate the coefficients of the ARIMA model

The coefficients of the ARIMA model are estimated by using exact maximum likelihood functions. The acceptance of the calculated coefficients is determined based on their p-values. If a p-value is larger than the significance level of 0.05, then this coefficient is omitted, because having a p-value larger than 0.05 means insignificant.

When we model our S_1 data by using ARIMA(0,1,1), we find that the absolute value of the MA coefficient θ_1 is very close to 1, which is not desired. Mathematically, in an ARIMA model, if the absolute value of one of the coefficients is not smaller than 1, then this means that the model is not stationary. Absolute values just below 1 should be omitted as well. Since an ARIMA model implied by the investigation of the ACF and PACF is not unique, we tried different orders of p and q . Since a finite order MA process corresponds to an AR process with an order of infinity and very

high orders are usually not recommended, we decided to take the order of AR as low as possible. We found lowest possible order of AR to be either 5 or 6, justified also by diagnostic checking in the following step. The values of model coefficients, standard errors, and their p-values for S_1 are presented in Table-3.2.

Table 3.2: Model parameters, standard errors, and p-values for the data collected on asphalt road, at 1MHz repetition rate and 60km/h velocity

	Coefficient	std. error	p-value
ϕ_1	-0.8637	0.031	9.14×10^{-171}
ϕ_2	-0.7462	0.040	5.30×10^{-77}
ϕ_3	-0.5648	0.044	4.56×10^{-37}
ϕ_4	-0.4366	0.044	8.14×10^{-23}
ϕ_5	-0.2852	0.040	1.2×10^{-12}
ϕ_6	-0.1298	0.031	2.87×10^{-05}

The absolute values of coefficients are smaller than 1, which are plausible for ARIMA modelling. Moreover, standard errors of the coefficients are so small that they support the use of calculated coefficients, which is further supported by extremely small p-values. One should note that the p-values are raising as the coefficient order increases, which implies we need to stop increasing the model order at some point although theoretically we could go as far as infinity. In addition, mean and variance of innovations are found to be 0.000015 and 0.011608 respectively, which is satisfies initial assumptions of having zero mean and finite variance.

3.2.2.4 Diagnostic checking

Diagnostic checking aims to determine the suitability of the selected ARIMA model by checking whether the distribution of the residuals between the generated and observed data is white Gaussian. Whiteness of the residuals is measured by checking their ACF whereas their normality is tested by using Chi-Square test, which is a statistical hypothesis testing used to determine whether there is a significant difference between

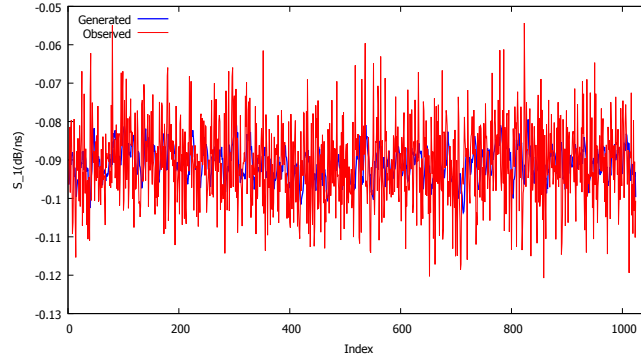


Figure 3.6: The generated and observed S_1 data

two distributions. The null hypothesis in deciding normality of the residuals is that residuals are distributed normally. Therefore, we need a high p-value in order to accept the null hypothesis.

The ACF values of the residuals between the generated and observed S_1 data are all smaller than the PACF value we used to determine the order p , which confirms the whiteness of the residuals. Moreover, the Chi-Square test yields 2.336 with the p-value of 0.331, which confirms normality of the residuals by accepting the null hypothesis.

Fig. 3.6 demonstrates the agreement between the generated and observed data.

3.3 Time-series Analysis

The ARIMA model is determined for the time series data of B_1 , B_2 , S_1 , S_2 , S_3 , X_1 , X_2 in asphalt and stones road at vehicle speeds of 20, 40 and 60 km/h with the 1 MHz sampling rate by following the procedure summarized in Section 3.2.2. The coefficients of the ARIMA model for asphalt and stone roads are presented in Tables 3.3 and 3.4 respectively.

The order of the ARIMA model is consistent over different roads and speeds. The absolute values of the model coefficients are mostly smaller on asphalt road than their counterparts on the stone road. Although this trend is not seen very clearly on all

Table 3.3: Asphalt road model parameters

		ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6	σ_a
B_1	1MHz – 20km/h	-0.8543	-0.7012	-0.5252	-0.3336	-0.1128		0.405679
	1MHz – 40km/h	-0.8352	-0.677	-0.5002	-0.3627	-0.2261		0.82202
	1MHz – 60km/h	-0.8029	-0.6544	-0.5079	-0.3508	-0.2255		0.321121
B_2	1MHz – 20km/h	-0.8258	-0.6602	-0.498	-0.3535	-0.1967		0.93862
	1MHz – 40km/h	-0.8302	-0.6491	-0.4891	-0.2943	-0.1491		1.784063
	1MHz – 60km/h	-0.7858	-0.6585	-0.5136	-0.3843	-0.2165		0.707014
S_1	1MHz – 20km/h	-0.8379	-0.658	-0.5168	-0.4239	-0.2532	-0.089	0.012895
	1MHz – 40km/h	-0.9111	-0.7001	-0.5263	-0.4384	-0.2869	-0.1203	0.018071
	1MHz – 60km/h	-0.8637	-0.7462	-0.5648	-0.4366	-0.2852	-0.1298	0.011608
S_2	1MHz – 20km/h	-0.8474	-0.6664	-0.4859	-0.2773	-0.1439		0.039388
	1MHz – 40km/h	-0.8166	-0.6411	-0.4789	-0.3119	-0.1947		0.029197
	1MHz – 60km/h	-0.8511	-0.7171	-0.5408	-0.4081	-0.1878		0.035163
S_3	1MHz – 20km/h	-0.9189	-0.7523	-0.6007	-0.4806	-0.2944	-0.1424	0.014258
	1MHz – 40km/h	-0.8656	-0.6903	-0.5499	-0.4369	-0.2867	-0.1367	0.021231
	1MHz – 60km/h	-0.8911	-0.7398	-0.5935	-0.4745	-0.2983	-0.1891	0.011881
X_1	1MHz – 20km/h	-0.822	-0.6769	-0.5056	-0.3022	-0.1716		0.128379
	1MHz – 40km/h	-0.8733	-0.7035	-0.5027	-0.3705	-0.1504		0.15146
	1MHz – 60km/h	-0.8697	-0.7207	-0.555	-0.3813	-0.1742		0.103611
X_2	1MHz – 20km/h	-0.8732	-0.7013	-0.5848	-0.3832	-0.2489	-0.1158	0.134837
	1MHz – 40km/h	-0.814	-0.6957	-0.5782	-0.4421	-0.3064	-0.1509	0.184517
	1MHz – 60km/h	-0.8501	-0.6559	-0.5815	-0.4355	-0.275	-0.1541	0.113635

of the results, considering that this holds for the majority of the data, we conclude that the absolute value of the model parameters increases as the roughness of the road increases. Smaller absolute values on ϕ parameters means lower oscillation in the data. The surface of the asphalt road is smoother than that of the stone road causing less variance on the data. In the scenarios of B_2 , S_1 , and S_3 we observe this behavior in the majority of the ϕ parameters. Although we observe a reverse trend in B_1 , the absolute values of the ϕ_1 parameters, which are the strongest among the rest of the ϕ parameters, tend to be smaller on asphalt road. Furthermore, we observe that the values of the model coefficients are independent of the vehicle speed.

Table 3.4: Stone road model parameters

		ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6	σ_a
B_1	1MHz – 20km/h	−0.8378	−0.6659	−0.4766	−0.2748	−0.0923		1.045599
	1MHz – 40km/h	−0.8708	−0.6395	−0.4922	−0.3093	−0.1424		0.7672
	1MHz – 60km/h	−0.8452	−0.6319	−0.468	−0.3276	−0.127		1.003024
B_2	1MHz – 20km/h	−0.8599	−0.7729	−0.5826	−0.3802	−0.20775		1.188878
	1MHz – 40km/h	−0.8714	−0.6874	−0.5391	−0.3642	−0.1876		0.94593
	1MHz – 60km/h	−0.8659	−0.6905	−0.5231	−0.3166	−0.158		0.8696
S_1	1MHz – 20km/h	−0.879	−0.7373	−0.5942	−0.4626	−0.2988	−0.1834	0.022527
	1MHz – 40km/h	−0.8946	−0.6897	−0.5611	−0.376	−0.304	−0.1589	0.019566
	1MHz – 60km/h	−0.8437	−0.7599	−0.5414	−0.452	−0.2409	−0.1173	0.023419
S_2	1MHz – 20km/h	−0.8353	0.6609	−0.5284	−0.3239	−0.1941		0.019722
	1MHz – 40km/h	−0.9174	−0.7272	−0.5607	−0.3705	−0.1727		0.017472
	1MHz – 60km/h	−0.8761	−0.6924	−0.4917	−0.3099	−0.1235		0.020404
S_3	1MHz – 20km/h	−0.8791	−0.7665	−0.6361	−0.4845	−0.2987	−0.1495	0.012456
	1MHz – 40km/h	−0.829	−0.6484	−0.5673	−0.3923	−0.3037	−0.1923	0.012693
	1MHz – 60km/h	−0.8533	−0.722	−0.5561	−0.4458	−0.3599	−0.1681	0.008244
X_1	1MHz – 20km/h	−0.7792	−0.6249	−0.4572	−0.3403	−0.1716		0.27785
	1MHz – 40km/h	−0.8345	−0.6919	−0.5344	−0.355	−0.1854		0.2304
	1MHz – 60km/h	−0.8977	−0.787	−0.5027	−0.3602	−0.1727		0.253589
X_2	1MHz – 20km/h	−0.8498	−0.6179	−0.4749	−0.3517	−0.2795	−0.1588	0.1272
	1MHz – 40km/h	−0.8317	−0.6884	−0.6041	−0.3946	−0.2556	−0.1353	0.1246
	1MHz – 60km/h	−0.8422	−0.7311	−0.584	−0.472	−0.2756	−0.1528	0.130668

Chapter 4

CONCLUSION

We investigated two distinct UWB channel models in this thesis. The first UWB channel model for IVWSN within the engine compartment of the vehicle by collecting an extensive amount of data for 19×19 links for different types and conditions of the vehicle: Fiat Linea with engine off, Fiat Linea with engine on, Peugeot Bipper with engine off. We derive the distributions, parameters and dependence relations related to the UWB engine compartment channel model including the path loss and power variation around the expected path loss; the distribution of the cluster inter-arrival times and the dependence of the cluster amplitude and cluster decay rate on the cluster arrival times in the SV model; and the probabilistic distribution of the variation of the observed PDPs around the SV model. We generate the simulation model for the UWB channel within the engine compartment and validate the model by comparing the received energy and root mean square delay spread obtained from the simulation and experimental data.

The small variations of the model parameters for different types and conditions of the vehicle demonstrate the reliability of the proposed simulation model built based on an extensive set of measurements.

In the second channel model we analyze the temporal variation of the beneath the chassis UWB channel based on ARIMA model. The clustering phenomenon in the PDPs collected beneath the chassis of the vehicle has been previously represented by using modified SV model. We propose a novel time variation model for the time series data corresponding to the parameters of the SV model including its cluster arrival times, cluster amplitude and ray amplitude decay rate. Either ARIMA(5,1,0) and ARIMA(6,1,0) have been demonstrated to fit the data collected at different vehicle

speeds on asphalt and stone roads. The absolute values of the model coefficients are demonstrated to be mostly smaller on asphalt road than their counterparts on the stone road while exhibiting independent behavior over several vehicle speeds.

In the near future, we plan to investigate the time-series UWB channel model for various scenarios, such as under acceleration and different impulse train repetition rates.

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