Decomposition Based Congestion Analysis of the Communication in B5G/6G TeraHertz High-Speed Networks

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***Abstract*—The New MAC mechanism plays a key role in achieving the needed requirements of the B5G/6G radio technology and helps to avoid high-speed frequency issues and limitations. With the help of the ns-3 simulator, we generated 42 different cases for the purpose of analyzing the impact of the network load on the overall effective transmission rate. Therefore, the use of the data-adaptive decomposition method the Empirical Mode Decomposition (EMD) on our non-stationary system benefits in the extraction of the important meaningful components. However, due to the highlighted direction dependency finding of EMD, Ensembled EMD (EEMD) being direction independent shows better performance on our data series. The extracted trend based on the proposed method matches the fitting curve, while the fitting curve parameters can be clusterized into 2 main clusters congested and non-congested cases of the radio channel throughput signal.**

***Index Terms*—Tera-Hertz technology, 6G, Beyond 5G, Empirical Mode Decomposition, Ensemble Empirical Mode Decomposition, Intrinsic Mode Function**

I. INTRODUCTION

WITH the rapid proliferation of the Internet of Things (IoT), an expansive multitude of end devices has emerged, necessitating the advent of a novel wireless generation capable of facilitating seamless connectivity with an exceptionally high bit rate. B5G/6G technology harnesses the potential of Terahertz bands, enabling the attainment of extraordinary data transfer speeds reaching several Tbps, accompanied by an impressively low latency of just 1 ms [5]. However, the effective management of the spectrum allocation encounters formidable challenges attributed to molecular absorption loss as well as the intricate interplay of diverse natural factors, encompassing pressure, relative humidity, and temperature, which profoundly impact the propagation environment [7]. The rapid growth of the Internet of Things (IoT) has resulted in an unprecedented number of connected devices, creating a demand for a new wireless generation that can handle the increasing volume of data and provide seamless connectivity. The current wireless technologies face limitations in terms of capacity and bandwidth, which hinder their ability to support the IoT ecosystem effectively. However, the emergence of B5G/6G and the utilization of Terahertz bands hold great promise in overcoming these limitations. Terahertz frequencies offer a significantly higher data rate potential, enabling transmission speeds in the range of several Tbps. By harnessing the Terahertz bands, the new wireless generation can address the constraints of current technologies, providing the necessary bandwidth and capacity to accommodate the expanding IoT landscape.

The Adaptive Directional Antenna Protocol for THz networks (ADAPT) protocol represents a pioneering Medium Access Control (MAC) mechanism specifically designed for the Terahertz frequency domain. ADAPT has demonstrated remarkable performance improvements, exhibiting a remarkable throughput of approximately 120 Gbps within a single radio cell accommodating 50 Mobile Terminals (MT) [3]. However, it should be noted that ADAPT does encounter certain limitations when operating in a heavily loaded network environment [3, 10]. In scenarios characterized by heightened congestion, the transmission time gradually escalates, thereby adversely affecting the overall channel throughput. Hence, our investigation seeks to make a significant contribution to the advancement of techniques for analyzing non-stationary and nonlinear THz throughput signals. By doing so, we aim to enhance network congestion state detection and overall performance optimization in real-world applications. The main highlights of the paper can be summarized as follows:

- The generation of ADAPT data along with the introduction of the utilized decomposition methods.
- The utilization of diverse decomposition methods with various analyses.
- The data series undergoes decomposition-based trend extraction, followed by the clusterization of the extracted trend parameters.

Chapter two of this work provides an overview of pertinent literature related to the decomposition and the current study. Chapter three explores the characteristics of the decomposition methods and the ADAPT MAC mechanism. Moving on to chapter four, an analysis is conducted on the performance of EMD and EEMD. Lastly, chapter five presents a comprehensive summary and conclusion of the findings derived from the study.

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II. Related Work

Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD) are two signal processing methods used to decompose non-stationary and nonlinear signals Intrinsic Mode Functions (IMFs). Therefore, the authors in [11] aim to compare those two methods in the analysis of a seismic signal. The results of this work show that the time-frequency spectrum obtained through EEMD more accurately reflects real geological conditions as compared to EMD. Other work has been done on the same topic using EMD, EEMD, and Variational Mode Decomposition (VMD) in [6] for chatter detection in milling. The researchers compared the three methods and found that EEMD and VMD were more effective than EMD. EMD has been widely used for trend extraction in various fields, it is a powerful tool for analyzing non-stationary and extracting meaningful information from them. However, trend extraction methods using the IMFs might differ.

In [4] the authors decompose the IMFs into two parts, the trend one of them. Moreover, in [2] the authors proposed a method for extracting the trend. The method involves decomposing the signal into IMFs, and then fitting the extracted trend component using the least squares method. The proposed method was validated using experimental data and was found to be effective in identifying the trend of the cement-burning zone flame temperature. Research conducted in [12] compared EMD and EEMD and revealed that EMD suffers from mode mixing, leading to inaccurate extraction of signal characteristics. On the other hand, EEMD successfully extracts meaningful components and exhibits superior performance in fault diagnosis for rotating machinery, as demonstrated through simulations and real-world applications. In a related study, another group of researchers investigated EEMD's effectiveness in overcoming mode mixing by introducing white noise [13]. EEMD accurately decomposed signals into distinct IMFs, thereby enhancing time-frequency analysis and providing more realistic time-frequency spectra in geology applications.

The team in [14] introduced a hybrid denoising method that combines thresholded IMFs with data-driven VMD, proving highly suitable for non-stationary seismic signals with reduced noise sensitivity. Additionally, [15] demonstrated that EEMD outperforms EMD and VMD for calculating respiration rates from PPG signals, achieving over 90% accuracy with an average error rate of 1 rate/minute. EEMD shows potential in simplifying sensor devices for accurate RR calculation.

III. Applied Methodology

In our research work, we collected data of the new MAC mechanism ADAPT that is compatible with the first standardization for the THz physical layer defined in IEEE 802.15.3d [3]. For our simulation, we employed the pre-existing example available in the second version of *TeraSim*, a platform designed specifically for simulating extremely high frequencies, integrated into the *ns-3* simulator. In our study, we utilized the ADAPT MAC protocol within the Macroscale scenario to evaluate its performance in the context of THz frequencies. Along with the new proposed parameters [9] the overlapped sectors and the step parameters, we generated 42 different cases. 7 different number of steps based on the properties mentioned in [9] (s = 1, 7, 11, 13, 17, 19, 23), 2 different topologies: the centered topology where the MT are distributed closer to the Access Point (AP), and the random uniform where the MT is distributed uniformly around the AP. The radius of the area under consideration is determined to be 18 meters, and there are 30 sectors within this area. With these values established, it becomes evident to calculate the population density parameter (ρ = n/A $[m^{-2}]$), where n represents the population count and A denotes the area of the circle.

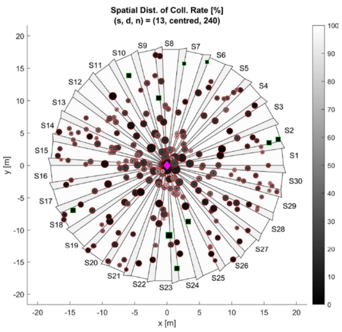

Fig. 1. Spatial distribution of the collision rate (step, d, n) = (13, 1, 240)

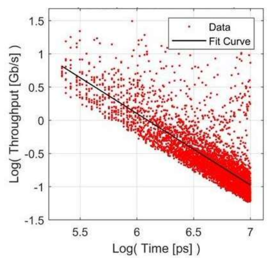

Fig. 2. Throughput vs. time (step, d, n) = (13, 1, 240)

We used 3 different numbers of MT ($n = 60, 240, 960$) having the overlapped ratio fixed $m = 0.3$ (see Fig. 1). The behavior of the throughput is particularly intriguing, as its distribution exhibits a gradual decrease over time, as illustrated in Fig. 2. This trend is further confirmed and supported by the fit curve, which aligns with the decreasing pattern of the throughput as time progresses. The representation declines the nature of the THz throughput, and the fit curve provides a mathematical model that captures and validates this diminishing trend. The combination of empirical evidence from the distribution plot and the fit curve's analytical support strengthens the significance of this observation.

A. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) can be applied to a nonlinear and non-stationary signal. Although, it is a sophisticated method for features extraction [1]. EMD decomposes the signal into a finite number of IMFs plus the residual, the decomposition process involves identifying all extrema of the signal *X(t)* and connecting them with the help of cubic splines to obtain an upper and a lower envelope [1]. It calculates the mean of the upper and lower envelope *m1*, then subtracted from the original signal to obtain the first component *h1* (1). However, the resulting IMF most of the time is not the right IMF because it does not satisfy the necessary conditions. Therefore, the sifting process is used and repeated to refine the IMF by eliminating riding waves, making it more symmetric and smoothing uneven amplitudes.

$$X(t) - m_1 = h \tag{1}$$

By doing so, the resulting IMF is then subtracted from the original signal to obtain a residue signal (2) where $c1$ is the IMF after j sifting times.

$$X(t) - c_1 = r_1 \tag{2}$$

IMF1 is then decomposed into the second IMF using the same process. This process is repeated until the last residual. However, like any other processing method, EMD struggles with some limitations that should be considered such as the end effect where the first and the last points most of the time are not the extreme values. Also, the mode mixing limitation occurs when the IMF components overlap and cannot be separated from each other. It can happen when the signal has multiple scales of variation, leading to a difficult interpretation of the IMF components [8].

B. Ensemble Empirical Mode Decomposition

Ensemble Empirical Mode Decomposition (EEMD) is an advanced technique designed to enhance the traditional EMD method, specifically tailored for the analysis of non-stationary and nonlinear signals. One of the key challenges faced by EMD is the presence of the mode mixing problem, which can result in inaccuracies during signal analysis. To overcome these limitations, EEMD introduces a novel approach by incorporating an ensemble of white noise into the original signal before applying the EMD method. This addition of white noise ensures that each iteration of the EMD process produces slightly different results, effectively mitigating the mode mixing problem.

The EEMD process involves several steps: Firstly, the original signal is combined with white noise, leading to the generation of multiple noisy versions of the signal. Subsequently [8], the traditional EMD method is applied independently to each of these noisy signals, extracting a set of IMFs from every iteration. Finally, the IMFs obtained from all iterations are averaged, yielding the final IMFs. Through this ensemble approach, EEMD successfully overcomes the limitations of traditional EMD and improves the accuracy of the extracted IMFs, representing more faithfully the underlying components of the signal. This enhancement proves particularly valuable when dealing with intricate and non-stationary signals, enabling more dependable time-frequency analysis and extraction of signal characteristics.

IV. Measurement Scenario and Analysis of the Mobile ADAPT System

Since non-stationary and nonlinear systems in high-speed wireless communication networks require special signal processing methods, EMD can be a suitable approach. Consequently, we have decided to use EMD to decompose the throughput data of ADAPT and analyze the obtained results.

A. EMD Decomposition-Based Throughput Analysis

To observe the impact of applying the EMD on throughput analysis, we decided to apply EMD in a direct way from $time_{start}$ to $time_{end}$, and then inversely from $time_{end}$ to $time_{start}$. The results of this experiment show the resulting IMFs of the direct and inverse methods plotted versus the time (Fig. 3 and Fig. 4).

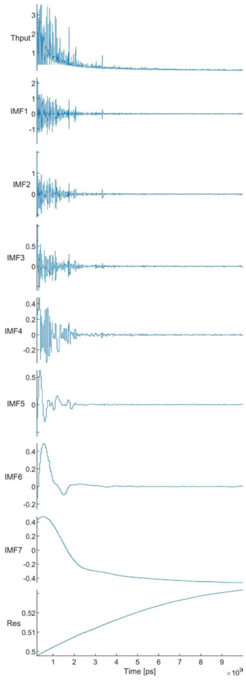

Fig. 3. Direct EMD on Throughput vs. time

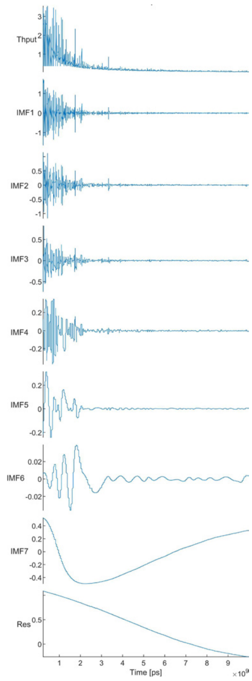

Fig. 4. Inverse EMD on Throughput vs. time (c = 0.48)

The experiment was in the case where the $step = 7$, the topology was centred, and $n = 960$. Our observation from the results was that the IMFs generated by the direct and inverse methods were significantly different, despite having different amplitudes for the same IMFs. This difference was further confirmed by a correlation coefficient of less than *0.5* ($c = 0.48$), which indicates that EMD is direction-dependent.

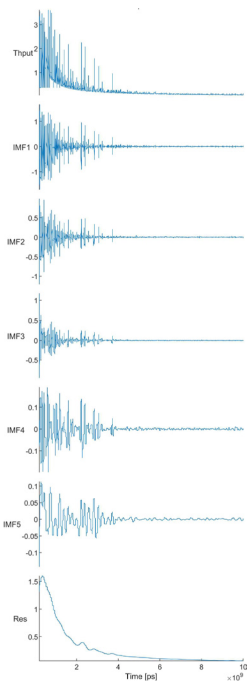

Fig. 5. Direct EEMD on Throughput vs. time (Noise = 0.05)

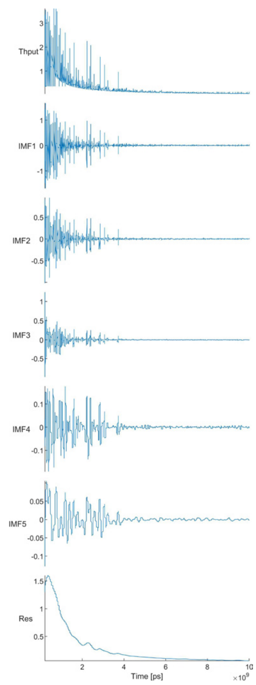

Fig. 6. Inverse EEMD on Throughput vs. time (c = 0.994)

The experiment was repeated using EEMD with 5 percent white noise in cases where we have $step = 23$, the topology centred, and $n = 960$. The IMFs generated by the direct and inverse methods were identical, despite having the same amplitude (Fig. 5 and Fig. 6). This finding was confirmed by a high correlation coefficient $c = 0.994$, which indicates that EEMD is direction-independent.

We came up with the idea of using the fast Fourier transform on the IMFs resulting from EMD to extract the frequency information. It is evident that the FFT gives adjacent sub-frequency bands in log2 of the frequency for adjacent IMFs, which is reminiscent of the dyadic filter bank (See Fig. 7 the throughput signal in case where we have $step = 11$, random uniform topology and $n = 960$, and Fig. 8 in case $step = 7$, centered topology and $n = 960$).

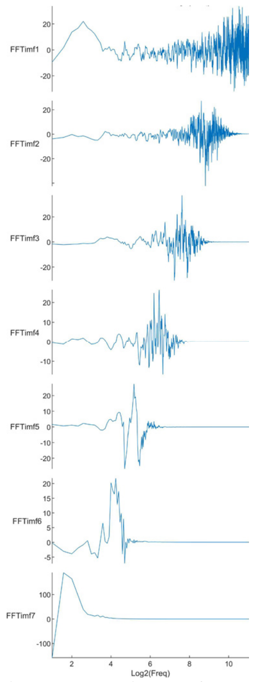

Fig. 7. Fast Fourier transform on IMFs (step, d, n) = (11, 2, 960) vs. frequency

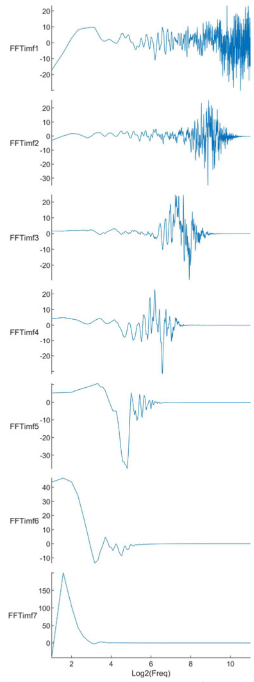

Fig. 8. Fast Fourier transform on IMFs (step, d, n) = (7, 1, 960) vs. frequency.

B. Analysis of Data and Trend Extraction

For extracting the trend using the IMFs components, one approach is, to sum up, each k consecutive IMFs together with the residual component (as Fig. 9 shows). It is obvious that if the number of IMFs included in each sum is precisely equal to k, then the resulting trend will exactly match the original throughput signal.

To select the optimal trend among the potential options, we suggest employing a Root Mean Square Error (RMSE) calculation to compare each trend candidate against the original signal. The trend component with the smallest non-zero RMSE will be chosen as the final trend. This approach ensures that the selected trend is as close as possible to the original signal. The RMSE values are plotted versus $trend_k$ in centered topology, $step = 23$, and $n = 960$ (Fig. 10).

By analyzing this graph, it becomes possible to visually identify the trend component with the smallest non-zero RMSE and thus select the optimal trend for the given dataset.

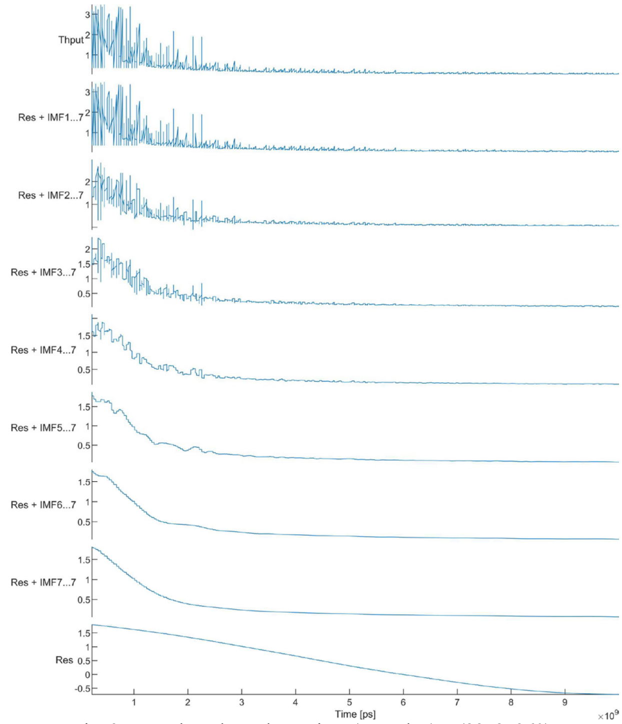

Fig. 9. IMFs-based trends vs. time (step, d, n) = (23, 2, 960)

The visualization of RMSE values versus $trend_k$ for all *42* cases simultaneously allows us to observe that the chosen $trend_k$ differs from case to case (Fig. 11). By examining this graph, we can identify that there is no single trend component that performs optimally across all cases. Instead, the optimal trend varies depending on the specific dataset under consideration.

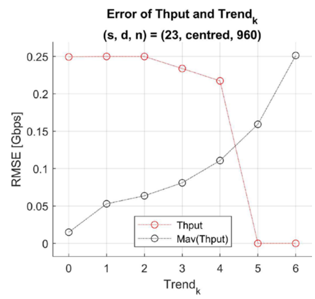

Fig. 10. The error of throughput and trend

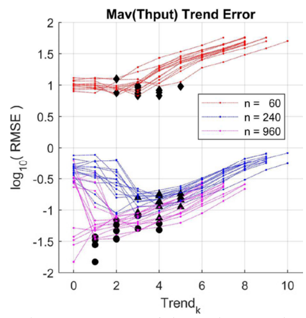

Fig. 11. RMSE of throughput and IMF-based trend

Therefore, it is important to perform an individualized analysis for each dataset to determine the appropriate trend component. This approach ensures that the chosen trend is both accurate and effective for a given dataset, leading to more reliable results and better decision-making.

The ability to observe and understand the variability in RMSE and $trend_k$ across different cases highlight the importance of customizing analysis to specific datasets and avoiding generalizations.

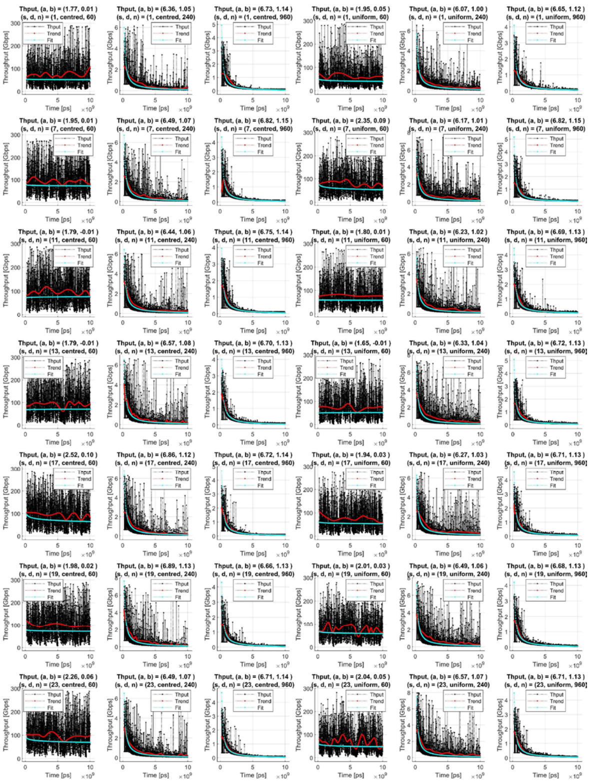

Fig. 12. Dependence of throughput, trend, and fit curve on time

To enhance our analysis, we included a fit curve of the original throughput dataset in addition to the chosen trend and the original data. This fit curve provides a visual representation of the overall trend in the data and facilitates the comparison of the chosen trend with the original signal (Fig. 12 presents a plot showing all 42 cases together).

Upon examining this graph, it is apparent that the chosen trend and the fitting curve are quite similar in the majority of cases. This similarity indicates that the selected trend is an accurate representation of the underlying trend in the data. However, there are some cases where the chosen trend deviates significantly from the fitting curve. These deviations may be the result of outliers or other anomalies in the data. By comparing the chosen trend and the fitting curve in this manner, we can gain a more comprehensive understanding of the data and make more informed decisions based on the analysis results.

Upon applying the fitting curve to the original signal, we meticulously extracted the fitting parameters and subsequently generated a scatter plot to provide visual insight into the outcomes of parameters a and b (as depicted in Fig. 13). Notably, the red-highlighted cluster is associated with instances of lower congestion levels, while the black cluster corresponds to more congested cases.

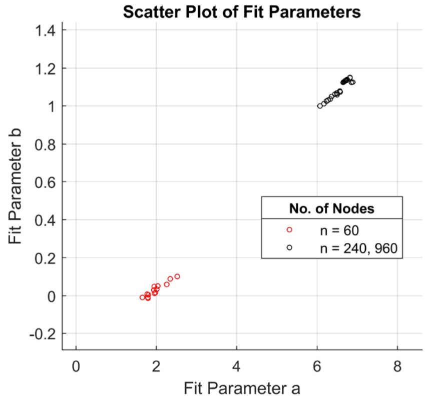

Fig. 13. Scatter plot of the fit parameters

These findings strongly imply that the fitting parameters, specifically parameters a and b, hold promising potential as valuable indicators for discerning and characterizing network congestion states. Such observations signify the scientific relevance and significance of the proposed methodology in understanding and quantifying the complexities of network congestion in our study.

V. Conclusion

The analysis of our throughput data using the EMD method in both left-to-right and right-to-left directions revealed a strong dependence on the processing direction. This dependence is likely attributed to the end effect issue, which affects the EMD's performance. In contrast, when applying the EEMD method, the results indicated its independence from the processing direction, showcasing its superiority in mitigating such issues. Furthermore, the trend extracted through our proposed method (in Section 3, Subsection B) demonstrated a remarkable correspondence with the fitting curve, showcasing the reliability and accuracy of our approach in analyzing radio channel throughput signals. This alignment between the extracted trend and the fitting curve underscores the effectiveness of our proposed method. Additionally, by examining the fitting curve parameters obtained from our method, we observed the emergence of two distinct clusters. These clusters corresponded to the congested and non-congested states of the radio channel throughput signal. This exciting finding implies that our proposed method not only effectively analyzes radio channel throughput signals but also enables precise detection and differentiation of various network congestion states.

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the clock domain switch the synchronization accuracy can be drastically improved.

Regarding future work, the synchronization error of the master and slave device can be further reduced with fine tuning of PI controller or with the implementation of a more sophisticated solution such as Kalman-filtering. Another possible future research direction would be the evaluation and measurements of the different LOS and NLOS scenarios and the characteristics of the distance between the master and slave device. Furthermore, as the UWB technology has significant limitations beyond a certain distance, there is some initial research on a multi-hop UWB PTP system. Such a system can provide clock synchronization on the order of 10 ns over many times the UWB radio range. However, in this case, the synchronization errors are accumulated, offering an exciting research topic.

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Currently, she is engrossed in pursuing a Ph.D. degree in the prestigious Faculty of Informatics at the University of Debrecen, Hungary, where she continues to display her dedication to advancing knowledge in her field. Since the beginning of her Ph.D. studies, she has been dedicated to advancing her research in cutting-edge areas of the telecommunications industry, with a primary focus on upcoming 6G/Beyond 5G (B5G) high-speed wireless communication systems and communication in the TeraHertz frequencies. Her research involves conducting thorough analyses and investigations into the limitations and challenges associated with such new frequencies. Through her academic pursuits, she aims to contribute valuable insights to the field and play a significant role in shaping the future of high-speed wireless communication systems in the 6G/B5G era.

Zoltan Gal is currently an associate professor at the Faculty of Informatics, University of Debrecen, Hungary. He earned MSc in electrical engineering and computer science from the Technical University of Timisoara, Romania and PhD in informatics sciences from the University of Debrecen. His scientific interest is focused on distributed processing and communication systems, sensor technologies and services in the Internet of Things. He was the CIO of his institute for 20 years and developed the university-level metropolitan area highs-speed data network and services with over 10k Internet nodes. He is Cisco Certified Network Professional lecturer since 1999 and taught over five hundred network professionals in the field. Starting in 2015 he is head of the Centre of High-Performance Computing at his university. He is an IEEE member since 1996 and published over one hundred twenty scientific conferences and journal papers: He supervises his own R&D&I project called QoS-HPC-IoT Laboratory.