Realizing Future Intelligent Networks via Spatial and Multi-Temporal Data Acquisition in Disdrometer Networks

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***Abstract*—Data acquisition and qualitative precipitation estimation (QPE) via disdrometers play an important role in estimating rain-induced attenuation in wireless networks. However, existing disdrometer observations do not provide sufficient information for modelling intelligent wireless networks. The design of intelligent wireless networks requires that QPE parameters for a location be known at different epochs. This requires that disdrometers with spatial variability should be capable of multi-temporal QPE observations. A disdrometer architecture that addresses this challenge is presented in this paper. The proposed multi–temporal disdrometer incorporates a computing payload for storing QPE related data at multiple epochs. Performance evaluation shows that the use of the proposed multi–temporal disdrometer in QPE related data acquisition increases data suitable for QPE related modelling by up to 52.2% and 49.4% in the short term and long term respectively.**

Keywords: Remote Sensing; Quantitative Precipitation Estimation; Disdrometer Networks, Size of modelling data; Disdrometers

I. INTRODUCTION

Data acquisition for precipitation studies plays an important role in wireless network design. Wireless systems that incorporate earth to space links transmitting in high frequency bands are subject to rain attenuation [1-2]. Rainfall studies require equipment enabling the determination of key parameters. The disdrometer is an important instrument that is used to study rainfall pattern and acquiring rain data.

The disdrometer enables the determination of important parameters such as the rain rate at a given location. The rain rate enables the computation of rain induced attenuation for space to earth network links with coverage over different regions [1-2].

The use of the disdrometer enables the observation of rain drop size distribution. It plays an important role in studying the microphysics associated with rain events at different locations [3-4]. The data acquired by the disdrometer is used for observing different rainfall events and microphysical behavior. Data acquired by the disdrometer is used for modelling rain attenuation in earth to space links.

Wireless networks benefit from the use of intelligent mechanisms and should be able to make decisions as regards data transmission while considering the effect of rain attenuation. This requires having access to rain data across time and space. The specific rain attenuation is currently determined largely via the radio propagation models from the international telecommunications union (ITU–R) model. The ITU-R model considers the geographical coordinates and the rainfall rates as important parameters in determining the rain induced attenuation. The model does not incorporate the temporal dimension (considering seconds, and milliseconds) for rainfall variation at a given geographical location. Instead, a uniform rainfall rate for a given location observed at an epoch is assumed and used for computing the rain attenuation. A temporal consideration of rainfall events and associated parameters is important for designing intelligent communication networks. This is because a temporal consideration enables the designer to obtain more information from data. This enables the intelligent networks to make more accurate intelligent network decisions. The ability to obtain information in the scale of seconds and milliseconds helps to make decisions as regards predicting rain attenuation that influences choice of operational parameters in intelligent wireless networks. This is beneficial for wireless networks where the latency is in the order of seconds and milliseconds duration.

A knowledge of the rainfall rate at a given location and epoch is important in making an estimate of rain-induced attenuation in wireless networks. Therefore, the disdrometer to be used in conducting studies with relation to the design of future networks should be able to acquire and process additional data. Data acquisition is important in modelling the temporal and spatial variation of rainfall and its influence on wireless networks. This requires novel disdrometer architecture. The novel disdrometer incorporates the ability to acquire rainfall data at multiple epochs i.e. considering the temporal dimension.

Disdrometer applications benefit from the incorporation of concepts from artificial intelligence and machine learning [5–9]. However, existing consideration has not incorporated the temporal dimension.

This paper discusses the capabilities required to enhance the disdrometer's data acquisition capabilities while enhancing rainfall prediction in relation to modelling rain induced attenuation in wireless networks.

The paper makes the following contributions:

1) First, the paper proposes disdrometer architecture with spatial and multi-temporal observation capability. The proposed disdrometer enables the evaluation of quantitative precipitation estimation (QPE) at a given location (spatial dimension) and multiple epochs (multi-temporal observation). The output of the proposed disdrometer enables the computation of desired parameters at selected epochs at a given location.

2) Second, the paper investigates how the use of the proposed disdrometer enhances QPE related data. This is because the use of the proposed disdrometer enhances the availability of data accessible for QPE. The paper formulates the total QPE related data

accessible before and after incorporating the proposed disdrometer architecture.

3) Third, the paper investigates the amount of QPE related data that is accessible from a disdrometer network. The disdrometer network comprises non-video and video disdrometers with and without the proposed architecture.

The remaining section of this paper is organized as follows. Section II describes the existing work on the use of the disdrometer in hydrometeor and rainfall modelling for wireless networks. Section III describes the problem statement being addressed. Section IV presents the proposed mechanisms and data processing framework. Section V formulates the performance model. Section VI discusses the simulation results. Section VII concludes the paper.

II. DISDROMETER USE - EXISTING WORK.

The study of rainfall and precipitation can be done via radar meteorology. Weather radar systems can be used to derive rainfall measurements and retrieval algorithms can be used to derive different parameters. Radar measurements can be combined via different mathematical relationships to obtain the rainfall rate, drop size distribution and specific attenuation. However, the use of weather radar to obtain these parameters is done in an indirect manner. This is done using expressions that enable the computation of the rainfall intensity from rain reflectivity as seen in [10-11].

The disdrometer plays an important role in determining the micro-structural properties of rainfall. This is because the disdrometer enables the measurement of rain rate and drop size distribution. The drop size distribution determined by the disdrometer is used to conduct the QPE. This estimation is useful in determining parameters such as specific rain attenuation.

Rainfall and precipitation studies require the acquisition of location specific information. For example, the rainfall distribution for Durban receives consideration in [12]. In [12], it is recognized that different statistical variations such as the Marshall-Palmer model, modified gamma distribution model and the tropical lognormal model can be used to model the rain drop size distribution.

The study in [12] focuses on rainfall modelling to determine the rain induced attenuation in wireless networks. The evaluation of the QPE for wireless networks is done with the aim of determining the associated rain-induced attenuation. This perspective can also be found in [13-16]. The study in [12] examines the process of estimating rainfall attenuation.

The estimation of rainfall attenuation requires having values for the rainfall drop-size distribution computed via the disdrometer. Additional parameters that are used are raindrop fall velocity, raindrop diameter interval, disdrometer sampling area and disdrometer sampling time (disdrometer hardware specific). In [15], the focus is on finding the rainfall attenuation for communication systems with frequencies beyond 10 GHz. The rainfall parameters are measured via a Joss-Waldvogel RD-80 disdrometer. Some of the parameters that are measured in this case are the rainfall rate, number of rainfall drops and the radar reflectivity.

Research on the role of QPE in wireless networks aim to determine the rainfall attenuation. However, the influence of rainfall is not only limited to the aspect of rain attenuation at a given location in wireless networks. It also varies with time i.e. temporal dimension. However, existing consideration neglects the temporal dimension and does not consider rainfall rate at multiple epochs (temporal dimension) and in a given location.

The disdrometer is used to conduct observations enabling the QPE. Significant factors such as high costs limit the use of disdrometer in QPE. Different approaches such as the use of synthetic rain fields have been recognized to be suitable. The use of synthetic rain fields also addresses challenges such as the occurrence of incomplete and uncertain information in rainfall measurement. However, the realization of synthetic rain fields requires the use of measured rain fall data and drop size distribution. The existing method considers only the spatial dimension i.e. location. This implies that the use of synthetic rain fields does not consider the temporal dimension i.e. seconds and milliseconds variation of rainfall events.

III. PROBLEM DESCRIPTION

This section describes the problem being addressed. The scenario being considered is that of a wireless network with earth to space or earth to aerial links. In an earth to space link, the space segment comprises communication satellites that transmit to a ground segment entity i.e. earth station. The earth to aerial link comprises high altitude platforms transmitting to a ground segment entity.

Let α denote the set of locations where satellite and high altitude platform i.e. aerial platforms provide network coverage.

$$\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_I\} \quad (1)$$

In addition, let f denote the set of operational frequencies for satellites and high altitude platforms.

$$f = \{f_1, f_2, \ldots, f_J\} \quad (2)$$

The current use of disdrometer enables the determination of the rainfall rate at the i^{th} location α_i , $\alpha_i \in \alpha$. The rainfall rate at the location α_i is denoted $r(\alpha_i)$. The rainfall rate at location α_i i.e. $r(\alpha_i)$ is used to determine the specific rain attenuation at frequency f_z , $f_z \in f$ where the specific rain attenuation for location α_i at frequency f_z is denoted $\gamma(\alpha_i, f_z)$.

The derivation of the specific rain attenuation $\gamma(\alpha_i, f_z)$ requires the parameters obtained from the disdrometer.

Given that a non-terrestrial platform has cognitive radio capability and utilizes different frequencies. The non-terrestrial platform also seeks to transmit in a frequency with the least rain attenuation. In this case, the cognitive radio aboard the non-terrestrial platform transmitting in frequencies f_1, f_2 and f_z; $f_1 \in f$, $f_2 \in f$ at an epoch $t_e, t_e \in t$, $t = \{t_1, t_2, \ldots, t_E\}$ should have access to the data on $\gamma(\alpha_i, f_1), \gamma(\alpha_i, f_2)$ and $\gamma(\alpha_i, f_z)$ at epoch t_e. Incorporating the role of the epoch t_e, the specific rain attenuation is re-written as $\gamma(\alpha_i, f_1, t_e), \gamma(\alpha_i, f_2, t_e)$ and $\gamma(\alpha_i, f_z, t_e)$ for frequency f_1, f_2 and f_z respectively.

The values of $\gamma(\alpha_i, f_1, t_e), \gamma(\alpha_i, f_2, t_e)$ and $\gamma(\alpha_i, f_z, t_e)$ are required to enable the non-terrestrial platform with cognitive radio capability determine the frequency suitable at each epoch i.e. with the least rain attenuation.

Furthermore, wireless network design requires a rain fading margin and should consider the value of the rainfall rate at a given location and epoch. Designing the link budget requires having knowledge of the probability that the rainfall rate is at a given value in a given location α_i for a specified epoch.

Since the rainfall rate is acquired for different locations, it is feasible to estimate the probability that the rainfall rate of a given value is obtainable at a certain location. In this case, the probability $P(r(\alpha_i))$ is that of obtaining a rainfall rate of $r(\alpha_i)$ at location α_i. However, to develop a more accurate estimation of the rain fade margin in the link budget; the probability of obtaining a rainfall rate $r(\alpha_i)$ at epoch t_e and denoted as $P(r(\alpha_i), t_e)$ is required.

The determination of the precipitation related parameters $\gamma(\alpha_i, f_1, t_e)$, $\gamma(\alpha_i, f_2, t_e)$, $\gamma(\alpha_i, f_z, t_e)$ and $P(r(\alpha_i), t_e)$ requires that the disdrometer should be capable of incorporating the temporal dimension in its observation procedure. However, the availability of these parameters is currently challenging from the perspective of QPE estimation.

The incorporation of the temporal dimension (time domain) into disdrometer measurement campaigns is required to realize $\gamma(\alpha_i, f_1, t_e), \gamma(\alpha_i, f_2, t_e), \gamma(\alpha_i, f_z, t_e)$ and $P(r(\alpha_i), t_e)$. This also leads to the emergence of more data from the disdrometer. In a case where multiple disdrometers are used, the data resulting from the measurement procedure becomes significant and should be processed to enhance decision making with the goal of improving the quality of data transmission in wireless networks. The considered wireless networks incorporate non-terrestrial communication nodes.

A representation of disdrometers and how they enable the realization of QPE related observation and computation is shown in Fig.1. The scenario on the left in Fig. 1 shows the disdrometer with existing capabilities. In this case, the disdrometer observes the rain rate at location 1 on Day 1. In this case, observation is conducted for three epochs i.e. t_1 , t_2 and t_3.

The figure on the right in Fig. 1 shows the case describing the disdrometer being proposed. In this case, the epochs t_1 , t_2 and t_3 now comprise sub-epochs (realized after incorporating the proposed temporal dimension). Each initial epoch comprises a total number of a sub-epochs. The proposed disdrometer can execute QPE related observation as presented in the scenario shown on the right in Fig.1.

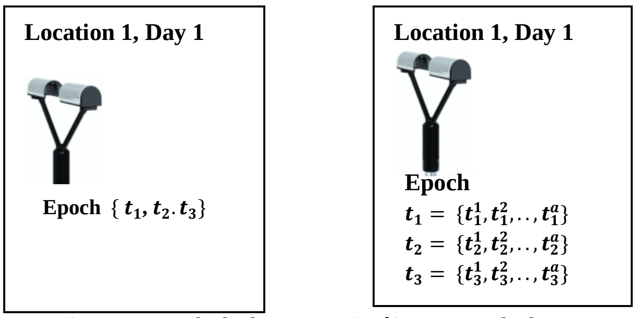

Fig.1: Scenarios with disdrometers (Left) existing disdrometers and (Right) proposed disdrometer capability.

IV. PROPOSED MECHANISM

This section presents the proposed mechanism that enables the conduct of disdrometer measurement campaigns while incorporating temporal dimension. The consideration of the temporal dimension is done for two reasons.

The first reason is that it enables an increased amount of QPE related data to be accessed by disdrometers. This has the benefit of increasing the amount of data accessible for the QPE modelling process. This is because the accuracy of QPE models aiming to predict rain induced attenuation improves when more data is available and accessible from disdrometers.

The second reason is to enable the determination of $\gamma(\alpha_i, f_1, t_e), \gamma(\alpha_i, f_2, t_e), \gamma(\alpha_i, f_z, t_e)$ and $P(r(\alpha_i), t_e)$. The goal of determining these parameters can be realized by incorporating time stamps in the disdrometer.

In monitoring the precipitation related parameters, a single disdrometer can be used as seen in [17]. The use of disdrometer networks is also feasible. Disdrometer networks enable the consideration of spatial and temporal variability in QPE.

Jameson *et al* [18] propose a disdrometer network comprising 21 optical disdrometers. The two-dimensional observation enables the consideration of different factors that interact in a rainfall event. The discussion in [18] considers the role of a disdrometer network in enabling a two dimensional study of rainfall events. The scenario in [18] considers 21 disdrometers with a separating distance of up to 100m. The disdrometer network is intended to cover a distance of up to 2.1 km.

The discussion in [19] utilizes a network of disdrometers to examine the variability of drop size distributions for rainfall in space. Raupach *et al* [19] have identified that disdrometer networks find widespread applications in the study of different precipitation patterns. The discussion in [19] examines the existing work from the perspective of QPE via disdrometer networks.

Disdrometer networks have the benefit of enabling the conduct of observations that capture the spatial variability of rainfall events. They also have the benefit of capturing the effect of spatial and temporal variability. This implies that rainfall events can be observed for similar epochs at different locations but challenging for close epochs at the same location.

However, the use of disdrometers does not incorporate time stamps in precipitation observation and estimation. QPE evaluation via disdrometer networks also enhances the resolution associated with precipitation estimation. This is especially in the case where disdrometer networks comprise multiple disdrometers covering a large geographical region with a high overall baseline. In such a disdrometer network, individual disdrometers have a temporal resolution that influences the sampling epoch and the duration associated with ongoing estimation.

The temporal resolution in the disdrometer is not related to capturing the details at the epoch of precipitation observation.

The use of a disdrometer network is recognized to be advantageous for QPE estimation. The disdrometer network being proposed considers the conduct of quantitative precipitation estimation in two contexts. The context being considered address challenges related to obtaining data from the proposed disdrometer for processing.

The rest of the discussion in this section is divided into two parts. The first part presents the architecture of the proposed disdrometer. The second part discusses data transmission aspects of the proposed disdrometer architecture.

A. *Proposed Solution – Disdrometer Architecture*

The proposed disdrometer incorporates a computing payload. The computing payload hosts resources and captures details associated with the onset of executing sampling algorithm aboard the disdrometer. The disdrometer also acquires details on the epochs associated with the completion of sampling.

The disdrometer also captures details on the following parameters: (i) epoch at which sampling begins, (ii) epoch at which sampling ends and (iii) delay between rain sensing and onset of sampling process for a given computation procedure. These additional details are associated with the precipitation related details and computed at the concerned epochs.

The architecture of the proposed disdrometer is shown in Fig. 2. In Fig. 2, the QPE payload hosts components that enable the monitoring of important rainfall parameters. It also hosts the sampling entity enabling the computation of QPE related parameters associated with different temporal resolution.

The computing payload hosts the resources enabling the aggregation of the details captured by the disdrometer. The computing payload supports the execution of algorithms and enables the creation of the precipitation record. The data storage entity stores the resulting precipitation record.

The precipitation record being stored in the data storage entity is transferred to the processing entity (not shown in Fig. 2 being external to the proposed disdrometer) via the communication module. The communication module interacts with wireless networks. It relates with external networks and ensures that a low amount of onboard disdrometer power is used for data transmission.

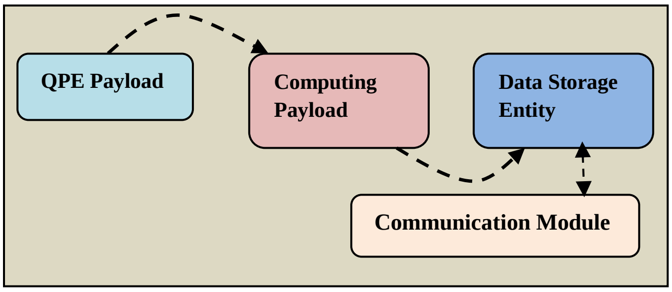

Fig. 2: Architecture block diagram of the proposed disdrometer.

The relations between sub–epochs in existing disdrometer and proposed disdrometer are shown in Fig. 3 and Fig. 4 respectively. Fig. 3 shows an observation epoch for the disdrometer. The disdrometer observes rainfall related data useful for QPE during the considered epoch. Fig. 4 shows the relations between epochs and sub–epochs as considered in the proposed disdrometer architecture. The single epoch in Fig. 3 has only one unique QPE related data point.

In Fig. 4, the single epoch previously considered in Fig. 3 now has three sub–epochs. Though, three sub–epochs have been considered in Fig. 4; multiple sub–epochs are possible. The case for three sub–epochs is only considered for the purpose of illustration in this paper. The proposed disdrometer architecture can support a variable number of sub– epochs. Each sub–epoch corresponds to a QPE data point.

Fig. 3: Observation epoch for existing disdrometer.

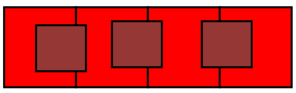

Fig.4: Observation epoch with three sub–epochs in proposed disdrometer.

The flowchart showing the functionality of the proposed disdrometer is presented in Fig. 5. The sub–epochs are specified in the scale of milliseconds while the epochs are specified in definition of real time i.e. the format of hours, minutes and seconds. In Fig. 5, the disdrometer is deployed in a location experiencing rainfall and selects multiple epochs lying within a given duration. The disdrometer observes QPE related data for a given sub–epoch and stores the data in onboard disdrometer memory. In the event that QPE related data is not observed and stored onboard disdrometer memory, the disdrometer tries to re–capture the concerned data. However, the epoch is flagged as lacking the required data in the onboard memory in the disdrometer when the start and stop epochs are no longer valid. The data observed by the proposed disdrometer are stored for later access onboard the disdrometer memory.

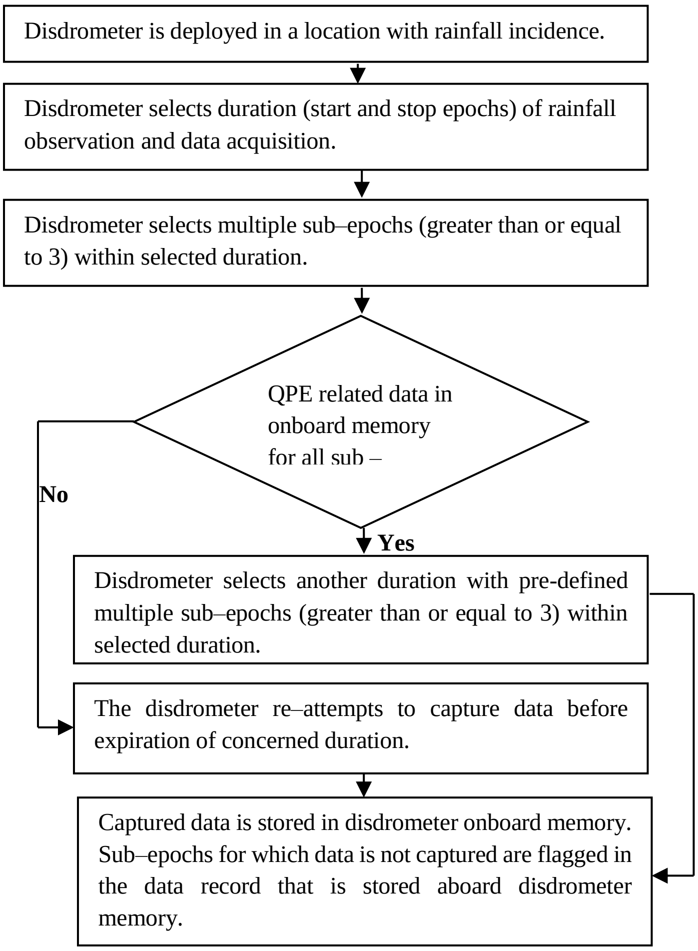

Fig.5: Flowchart of the proposed disdrometer.

B. Data Transmission Aspects

The considered disdrometer is installed in a location with wireless network coverage. The communication module aboard the proposed disdrometer transfers the precipitation record from the data storage entity to processing platform through terrestrial wireless networks.

The disdrometer's communication module can also transmit the precipitation record to wireless sensor networks. The transmission of data to the wireless sensor network is preferable because of the low power requirements. However, the communication module transmits the data to terrestrial wireless networks if wireless sensor networks are not detected.

The transmission of data to the wireless sensor network or terrestrial wireless network is intended to deliver the acquired precipitation record to the cloud computing platform. The precipitation record comprises information on the (i) precipitation related parameters evaluated by the disdrometer in the QPE procedure, (ii) epoch at which sampling begins and (iii) epoch at which sampling is completed. The data on the epoch at which sampling begins and at which sampling ends is stored in the proposed disdrometer.

The precipitation record is transmitted in the following manner. In the case where disdrometers transmit to the wireless sensor network; the wireless sensor network transmits the precipitation record to the terrestrial wireless network such as the long term evolution-advanced (LTE–A). The use of the wireless sensor networks is suitable when disdrometers have severe power constraints. This arises in the case where disdrometers are battery powered.

V. PERFORMANCE FORMULATION

The use of the proposed disdrometer in a standalone manner and in a disdrometer network enhances the QPE. This is considered due to two reasons. The first is that the proposed disdrometer acquires QPE data across spatial and multi-temporal dimensions. A multi-temporal dimension implies that the same parameter is observed across multiple epochs and averaged across multiple epochs for a given spatial dimension i.e. location. In existing disdrometers, only the spatial dimension is considered. This implies that QPE related parameters are evaluated for multiple epochs and averaged for a given location.

Performance formulation considers the size of QPE related data before and after using the proposed disdrometer architecture. Let d denote the set of disdrometers such that:

$$d = \{d_o, d_n\} \tag{3}$$

$$d_o = \{d_o^1, \dots, d_o^Q\} \tag{4}$$

$$d_n = \{d_n^1, \dots, d_n^P\} \tag{5}$$

d_o and d_n are the set of existing disdrometers and proposed disdrometers respectively.

Q and P are the total number of existing disdrometers and proposed disdrometers respectively.

The size of the data acquired by the q^{th} existing disdrometer d_o^q , $d_o^q \epsilon\, d_o$ at location α_i is denoted $N(\alpha_i, d_o^q)$. The data acquired by d_o^q at location α_i is that observed at different instants and averaged.

In the case of the p^{th} proposed disdrometer d_n^p , $d_n^p \epsilon\, d_n$, the size of the data acquired by the disdrometer d_n^p at location α_i and epoch t_e is denoted $N(\alpha_i, d_o^q, t_e)$. In this case, QPE related data is acquired by the disdrometer d_n^p at location α_i for multiple epochs. The variable $N(\alpha_i, d_o^q, t_e)$ describes the QPE related data acquired at epoch t_e by the disdrometer d_n^p at location α_i.

For the existing disdrometer (without spatial multi-temporal observation capability), the total size of acquired QPE data is denoted Z_1 and given as:

$$Z_1 = \sum_{q=1}^{Q}\sum_{i=1}^{I} N(\alpha_i, d_o^q) \tag{6}$$

The total size of QPE related data acquired when the proposed disdrometer (incorporating spatial multi-temporal resolution observation capability) is used is denoted Z_2 and given as:

$$Z_2 = \sum_{q=1}^{Q}\sum_{i=1}^{I}\sum_{e=1}^{E} N(\alpha_i, d_o^q, t_e) \tag{7}$$

VI. SIMULATION AND DISCUSSION

The simulation procedure investigates how the use of the proposed disdrometer enhances the size of the QPE related data that is obtained from the network. A high QPE data size is beneficial.

In the simulation procedure, video disdrometers and non–video disdrometers are utilized. Both disdrometers are considered with and without the proposed architecture. Simulation parameters are shown in Table I. It is assumed that disdrometers have varying data processing capabilities.

TABLE I: SIMULATION PARAMETERS

Parameter	Value
Number of non-video disdrometers (NVDs)	25
Number of video disdrometers (VDs)	25
Maximum size of QPE data from NVDs at an epoch(in absence of proposed mechanism)	9.03 Mbytes
Minimum size of QPE data from NVDs at an epoch(in absence of proposed mechanism)	0.30 Mbytes
Mean size of QPE data from NVDs at an epoch (in absence of proposed mechanism)	4.68 Mbytes
Maximum size of QPE data from VDs at an epoch(in absence of proposed mechanism)	194.12 Mbytes
Minimum size of QPE data from VDs at an epoch(in absence of proposed mechanism)	7.14 Mbytes
Mean size of QPE data from VDs at an epoch (in absence of proposed mechanism)	127.95 Mbytes
Maximum size of QPE data from VDs at an epoch(in absence of proposed mechanism)	190.03 Mbytes
Minimum size of QPE data from VDs at an epoch(in absence of proposed mechanism)	23.56 Mbytes
Mean size of QPE data from VDs at an epoch (in absence of proposed mechanism)	100.87 Mbytes
Maximum size of QPE data from NVDs at first epoch (incorporating proposed mechanism)	8.41 Mbytes
Minimum size of QPE data from NVDs at first epoch(incorporating proposed mechanism)	0.11 Mbytes
Mean size of QPE data from NVDs at first epoch (incorporating proposed mechanism)	4.23 Mbytes
Maximum size of QPE data from VDs at second epoch (incorporating proposed mechanism)	189.27 Mbytes
Minimum size of QPE data from VDs at second epoch (incorporating proposed mechanism)	0.88 Mbytes
Mean size of QPE data from VDs at second epoch (incorporating proposed mechanism)	93.43 Mbytes
Maximum size of QPE data from NVDs at second epoch (incorporating proposed mechanism)	6.83 Mbytes
Minimum size of QPE data from NVDs at second epoch (incorporating proposed mechanism)	0.57 Mbytes
Mean size of QPE data from NVDs at second epoch (incorporating proposed mechanism)	3.07Mbytes

The simulation parameters presented in Table I are used to investigate the size of QPE related data and the cummulative QPE related data before and after incorporating the proposed disdrometer architecture. The data is used for the conduct of the QPE related studies. The results for the size of QPE related data and cummulative QPE related data obtained via simulations is shown in Fig. 6 and Fig. 7 respectively. In Fig. 6 and Fig. 7, each epoch corresponds to a unique time instant.

The results in Fig. 6 and Fig. 7, show that the incorporation of the proposed disdrometer architecture (with multi-temporal dimension) capability enhances the QPE related data that is obtained from the disdrometer network.

The use of the proposed disdrometer architecture for a varying number of epochs (with up to 3 epochs) enhances the size of QPE related data in comparison to existing disdrometer architecture (existing scheme). This increases the QPE data available for modelling. The developed model is used for determining rain induced attenuation in wireless networks.

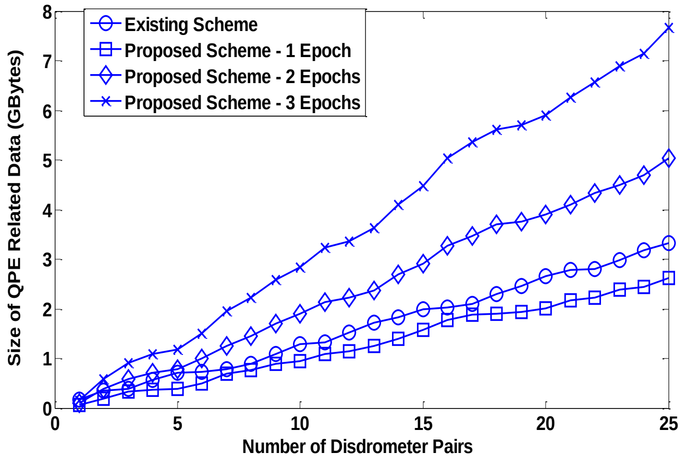

Fig. 6: Size of QPE related data before and after incorporating the proposed disdrometer architecture.

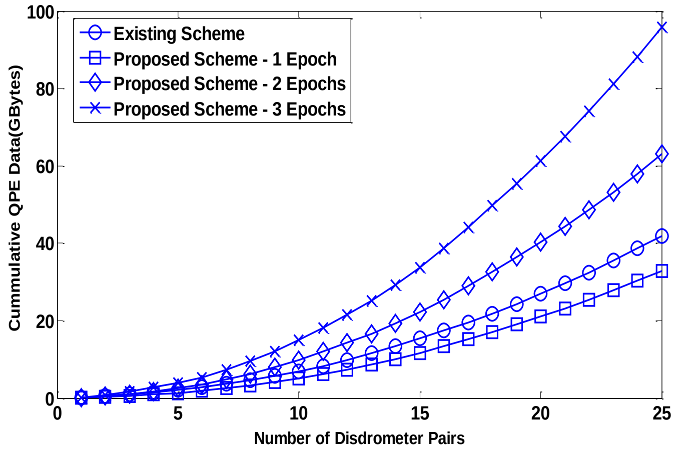

Fig. 7: Cummulative QPE related data before and after incorporating the proposed disdrometer architecture.

The result in Fig. 6 enables the increase in QPE related data to be determined for disdrometer pairs. In the simulation, a disdrometer pair comprises two disdrometers. The two disdrometers are a non-video disdrometer and a video disdrometer. In addition, the result in Fig. 7 enables the simulation procedure to evaluate how the use of the proposed disdrometer architecture enhances the total QPE related data that is accessed in the long term. This enables the simulation of the long term performance benefit of using the proposed architecture in disdrometer pairs.

Analysis of the performance results in Fig. 6 shows that the use of disdrometers with spatial and multi-temporal variability (Proposed Scheme–1 Epoch) instead of the disdrometers with existing spatial and temporal variability capability does not enhance the QPE related data. This is because the proposed disdrometer is not used to obtain QPE data at multiple epochs.

In addition, the simulation parameters show that the existing disdrometer has higher data sizes than the proposed disdrometer at only one epoch. However, in the case where the proposed disdrometer observes QPE related data at 2 and 3 epochs, the amount of QPE related data is obtained. Analysis shows that the use of the proposed disdrometer enhances the QPE related data by an average of 26.9% and 52.2% when the proposed disdrometer acquires QPE related data for 2 and 3 epochs in comparison to existing disdrometers respectively.

The result in Fig. 7 enables the increase in cummulative QPE related data to be determined for disdrometer pairs. This aspect of the simulation is suitable for determining the cummulative QPE related data obtained from the disdrometer network in the long run. In this case, the use of the proposed disdrometer architecture enhances the QPE related data obtained by 49.4% on average. Therefore, the use of the proposed disdrometers for 2 epochs and 3 epochs instead of the existing disdrometer increases the QPE related data obtained by 22.5% and 49.4 % on average respectively.

VII. CONCLUSION

This paper addresses the challenge of obtaining data from quantitative precipitation estimation procedures to improve rainfall modelling. It proposes an architecture that aims to equip disdrometers with multi-temporal and spatial variability capacity. The disdrometers with multi-temporal and spatial variability enable the observation of hydrometeors at the same epochs in a given location. The proposed disdrometer also develops an epoch based average of the concerned precipitation parameter for a given location. This advances the observation capability in existing disdrometers with temporal and spatial variability observation capability. The use of the proposed disdrometers increases the QPE related data obtained from disdrometer networks. This increases the ability to accurately model precipitation behaviour and also obtain additional parameters from the quantitative precipitation estimation procedure. Evaluation shows that the use of the proposed disdrometer instead of existing disdrometer in disdrometer networks enhances the QPE related data in the short term and in the long term. Future work aims to explore the technologies required to realize the physical design of the proposed disdrometer. Additional work also aims to investigate how the use of the proposed disdrometer enhances QPE related modelling.

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