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| Citation          | Kurdzo, James M. et al. "Quantification of Radar QPE Performance Based on SENSR Network Design Possibilities." 2018 IEEE Radar Conference [RadarConf18], April 2018, Oklahoma City, OK, USA, Institute of Electrical and Electronics Engineers, June 2018 © 2018 IEEE |
|-------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| As Published      | http://dx.doi.org/10.1109/radar.2018.8378551                                                                                                                                                                   |
| Publisher         | Institute of Electrical and Electronics Engineers (IEEE)                                                                                                                                                         |
| Version           | Author’s final manuscript                                                                                                                                                                                        |
| Citable link      | https://hdl.handle.net/1721.1/123998                                                                                                                                                                             |
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Quantification of Radar QPE Performance based on SENSr Network Design Possibilities

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Abstract—In 2016, the FAA, NOAA, DoD, and DHS initiated a feasibility study for a Spectrum Efficient National Surveillance Radar (SESNR). The goal is to assess approaches for vacating the 1.3- to 1.35-GHz radio frequency band currently allocated to FAA/DoD long-range radars so that this band can be auctioned for commercial use. As part of this goal, the participating agencies have developed preliminary performance requirements that not only assume minimum capabilities based on legacy radars, but also recognize the need for enhancements in future radar networks. The relatively low density of the legacy radar networks, especially the WSR-88D network, had led to the goal of enhancing low-altitude weather coverage. With multiple design metrics and network possibilities still available to the SENSR agencies, the benefits of low-altitude coverage must be assessed quantitatively. This study lays the groundwork for estimating Quantitative Precipitation Estimation (QPE) differences based on network density, array size, and polarimetric bias. These factors create a pareto front of cost-benefit for QPE in a new radar network, and these results will eventually be used to determine appropriate tradeoffs for SENSR requirements. Results of this study are presented in the form of two case examples that quantify errors based on polarimetric bias and elevation, along with a description of eventual application to a national network in upcoming expansion of the work.

Index Terms—radar, weather, rainfall estimation, error quantification

I. INTRODUCTION

The current S-band Weather Surveillance Radar 1988 Doppler (WSR-88D) network across the United States is approaching 30 years of age, resulting in extensive service life extension plans [1] and exploration of what a future network of weather radars would entail [2]. In addition, some of the FAA’s Airport Surveillance Radars (ASR; S band) and Air Route Surveillance Radars (ARSR; L band) are nearing end of life [3]. The Spectrum Efficient National Surveillance Radar (SENR) initiative seeks to replace these radar networks as part of the goal of vacating the 1.3- to 1.35-GHz radio frequency band for eventual auction and commercial use. Since the current ARSR network falls in this L-band spectrum, a new network of radars, either of a single design or a system of systems, would need to combine these three networks into non-L-band frequency bands. This initiative affords the opportunity to replace all three networks (and possibly the aging C-band Terminal Doppler Weather Radar) with modern radar systems, resulting in improved coverage density and other enhanced capabilities [3]–[5].

As part of the SENSR initiative, the participating agencies have developed preliminary performance requirements that, at a minimum, meet the existing capabilities, but in some cases also look to enhance capabilities in a future radar network. NOAA is leading the preliminary performance requirement development for the high-resolution weather mission (replacement of the WSR-88D network), including the quantification of enhancements to current capabilities in terms of existing products generated by the WSR-88D radars. One of the primary uses of weather radar is Quantitative Precipitation Estimation (QPE), a radar-derived estimate of rainfall that can be useful for flash-flood prediction and warning in areas sparsely covered by ground-based rain gauges [6]. With a host of variables that currently go into radar-derived products, any change in network design and radar capability will result in changes to the accuracy of QPE.

Depending on the eventual SENSR network design, there is the potential for increased density of radars with weather-sensing capabilities. Additionally, since current FAA radars utilize fan beams that decrease the vertical resolution of any weather sensing capabilities, any increase in resolution from the move to a pencil-beam architecture would greatly improve the efficacy of weather-related products. For example, if all or
many current ASR and/or ARSR sites were replaced with a multi-function radar with a pencil beam, an increase in low-level, high-resolution weather coverage would be the result. This low-level coverage could increase the accuracy of QPE (among other products) due to a sampling area closer to the ground and fewer areas being covered by radars too far away to sample below the melting layer. We must also consider potential changes in data quality for weather sensing, such as changes to polarimetric bias (or even the existence of dual-polarimetric capabilities), array size and beamwidth, sampling rates, etc. Quantifying these affects on existing and future products is key to ensuring NOAA’s missions are met.

The purpose of this study is to quantify the changes to QPE when certain radar variables are changed. Although not explicitly presented in this paper, the goal of this study is to eventually apply a regression-based model of these changes to possible future radar network designs in order to quantify a pareto front of cost-benefit for QPE in a new radar network [7]. By quantifying the error in QPE at different ranges, heights, resolutions, and rainfall rates, theoretical error can be quantified in a simulated SENSR network in order to assess the impacts of network and system design on QPE. Also as part of this study, but not presented in this paper, is a similar effort to quantify the impact of low-level scanning on tornado warning accuracy and benefit. The results of this part of the study will be presented in future publications.

This paper presents results of the first stage of this research in the form of two case studies with altered radar parameters. Polarimetric bias and minimum height above ground level are examined as possible degradation sources compared to existing QPE calculations. In the future, many cases will be combined to create a model that can be used to show both benefit and degradation of new network designs for QPE.

II. METHODOLOGY

A. QPE Calculation

Prior to the upgrade of the WSR-88D network to dual-polarization, precipitation rates and storm-total rainfall calculations were estimated solely via a Z-R relationship (where Z refers to the reflectivity factor and R refers to the rainfall rate). Z-R relationships assume that for a given reflectivity, only one rainfall rate is possible [8], [9]. Since this is clearly not an accurate assumption, hundreds of Z-R relationships were derived over decades of research, with a select few of these being used in real-time algorithms based on the type of rainfall currently occurring (e.g., convective, stratiform, tropical, etc. [9]). With the ability to discern between rain drop shapes using dual-polarization radar, the Z-ZDR-R and KDP-R relationships were developed (where ZDR refers to differential reflectivity and KDP refers to specific differential phase [10]). In the proper scenarios, Z-ZDR-R and KDP-R relationships resulted in the ability to more accurately estimate precipitation rates without having to switch between different Z-R relationships.

Additionally, a methodology for calculating QPE based on specific attenuation has been proposed and is planned for eventual implementation in the WSR-88D network and may serve as the QPE method for a future SENSR network due to concerns regarding polarimetric calibration [11]. QPE based on specific attenuation, or R(A), is impervious to polarimetric bias issues, partial beam blockage, attenuation, and wet radome challenges, but can be adversely affected by range to the target, cross-azimuth resolution, height above ground level, etc. The first case in this paper utilizes the Z-ZDR-R QPE method, while the second case utilizes the R(A) method.

The current iteration of the QPE rate calculation on the WSR-88D involves utilizing the output of the dual-polarimetric Hydrometeor Classification Algorithm (HCA) to determine the hydrometeor type. Depending on the calculated hydrometeor type, either a Z-R (Eq. 1, where \( a \) is a scalar value), Z-ZDR-R (Eq. 2), or KDP-R (Eq. 3) relationship is used. When a Z-R relationship is used, a scalar offset is applied based on the type of hydrometeor. Only the lowest scan elevation is used, although a dual-polarimetric “hybrid” scan is created using the next available scanning elevation in order to mitigate clutter contamination. In the cases presented in this study, only the base scan is used. The Z-ZDR-R relationship is used for rain, big drop, and heavy rain classes. A scaled Z-R relationship is used for wet snow, dry snow, graupel, and ice crystals. A KDP-R relationship is used for mixed rain and hail. The ground clutter, biological, and unknown classes are not assigned QPE values.

In the R(A) method, specific attenuation is used for all classes below the melting layer except for hail (where a KDP-R relationship is used), while scaled Z-R relationships are used within and above the melting layer. For our purposes, any Z values greater than 50 dBZ use a KDP-R relationship. The R(A) relationship is shown in Eq. 4, and is described in detail in [11]. \( A \) in Eq. 4 is calculated using Z and path integrated attenuation (based on differential phase, or \( \phi_{DP} \)) scaled by a parameter, \( a \).

\[
R(Z) = a(0.017)Z^{0.714} \tag{1}
\]

\[
R(Z, Z_{DR}) = (0.0067)Z^{0.927}Z_{DR}^{-3.43} \tag{2}
\]

\[
R(K_{DP}) = 44.0|K_{DP}|^{0.822}sign(K_{DP}) \tag{3}
\]

\[
R(A) = 4120.0A^{1.03} \tag{4}
\]

B. ORPG Simulator

In order to efficiently process WSR-88D data in a way that allows for both simple degradation techniques and accurate QPE calculations, the ORPG simulator described in [12] was used to process Level-3 estimates and products. The ORPG simulator is a MATLAB-based software suite designed to closely mimic the C-based operational ORPG used by the WSR-88D network. Although not all of the ORPG functionality is currently developed in the MATLAB framework, the key components necessary for QPE have been implemented. These
include data recombination from super resolution to legacy resolution, the dual-polarization preparation technique, quality indexing, the HCA, and a QPE module. By using a MATLAB-based computing environment, data are easily processed in a user-friendly fashion and are available for rapid quantification and storage for large projects such as the network design study this paper will lead into.

C. Data Degradation Techniques

Two variables are altered in this study and presented in the case examples in the following section: polarimetric bias and minimum elevation angle. By degrading these variables, the eventual goal of this study is to construct a regression-based model that can account for both degradation and improvement of these variables in order to determine an effective cost-benefit pareto front for each possible network design. Each variable is altered as far upstream in the ORPG simulator as possible in order to propagate the results through as much of the simulator as possible. Improvement is made possible by using the portion of the regression closest to existing radars and increasing the density in a future network design.

Polarimetric bias is applied by first utilizing the linearized versions of $Z_H$ (horizontal reflectivity factor) and $Z_{DR}$ to generate a linearized $Z_V$ (vertical reflectivity factor). In order to account for a range of possible polarimetric bias effects, including bias due to cross-polarization coupling, a Gaussian distribution of error about the mean with a standard deviation of 0.1 (chosen due to the assumed accuracy of polarimetric bias) is applied. To account for both $Z_H$ and $Z_V$ bias on the $Z_{DR}$ estimate, the positive half of the chosen bias is added to the $Z_H$ estimate, while the opposite half is subtracted from the $Z_V$ estimate. This allows the effects to be fairly applied to other estimates throughout the ORPG simulator chain. The components are then used to calculate a new $Z_{DR}$ at each
range gate, and $Z_H$ and $Z_{DR}$ are then converted back to decibels for use throughout the rest of the processing steps. It should be noted that zero polarimetric bias in the existing WSR-88D data is assumed, which is unlikely to be the case at all times. The minimum elevation angle degradation is applied by removing lower elevations and calculating the change in QPE. A mapping to the proper range is performed using a 4/3 earth radius model [8] and an interpolation to 1/120° of latitude/longitude. This resolution was chosen because it matches the GTOPO30 elevation data resolution that will be used in future iterations of this study [13].

III. RESULTS

The first case study examined in this paper is the 20 May 2013 Moore, Oklahoma EF-5 tornado, which was located serendipitously closely to the KTLX WSR-88D and is detailed in [14]. The chosen base scan time from KTLX is 2016:43 UTC. This time was chosen due to the wide range of hydrometeor types, including hail in the tornadic debris signature. The initial $Z$, $Z_{DR}$, HCA, and QPE outputs are shown in Fig. 1. This case is used to explore polarimetric bias error; it is important to note that the errors presented are relative to the original QPE values, not absolute errors. The second case study is the 30 June 2012 Mid-Atlantic derecho event. A 1-hour integrated QPE ending at 0356:41 UTC is used to compare the $Z$-$Z_{DR}$-R and R(A) methods, as well as different elevation scans using R(A). $Z$ at the approximate mid-point of the analysis period is shown in Fig. 3.

A. Polarimetric Bias

The first example is the addition of a +0.5 dB polarimetric bias. This example effectively increases $Z_H$ by a Gaussian distribution about 0.25 dB and decreases $Z_V$ by a Gaussian distribution about 0.25 dB. This is applied at each individual range gate and is propagated throughout the remainder of the ORPG simulator chain. The results are presented in Fig. 2, which includes the new $Z_{DR}$, QPE, and a scatter plot of the errors. It is important to note that the errors do not simply follow a curvilinear trend as might be expected from the $Z$-$Z_{DR}$-R relationship (Eq. 2). This is due to multiple factors; first, the Gaussian error distribution allows for a range of errors that represent a more realistic bias encountered by cross-polarization coupling. Additionally, Eq. 2 shows that there is a dependence on both $Z$ and $Z_{DR}$, meaning that the chosen application of bias (i.e., half to $Z_H$ and half to $Z_V$) will result in different effects. Finally, the application of different relationship equations (Eqs. 1-3) based on different hydrometeor classes will change the results independently of the equations themselves. Allowing the changes in $Z_H$ and $Z_V$ to propagate through the entire ORPG simulator chain models this in a relatively sensible way. This will become more important as lower elevation angles are removed, resulting in estimates originating from above the melting layer.

The errors shown in Fig. 2 are generally negative, which, due to the negative exponent applied to $Z_{DR}$ in Eq. 2, makes intuitive sense. The errors are also highest where heavy rain is reported in the HCA (Fig. 1), which is also where the largest drop sizes and hence highest $Z_{DR}$ values are located. Given that the negative exponent applied to $Z_{DR}$ in Eq. 2 is larger in magnitude compared to any other exponents in Eqs. 1-3, the areas with higher $Z_{DR}$ values would be expected to generate the largest errors. It is also worth noting that the areas of rain (low, but still positive $Z_{DR}$) also have negative errors, but they are roughly an order of magnitude less significant (also to be expected given the exponent values). Finally, the area of hail in the HCA output (which is an error in most areas for this case; much of the reported hail is actually tornadic debris) is unchanged, since QPE in hail is calculated using the $K_{DP}$-R relation, which has not been altered.

The errors shown spatially in Fig. 2 are also represented as a scatter plot in order to show the distribution of errors relative to $Z_{DR}$. This is important because the observed values can be compared with theory in order to show the disparity, and hence the usefulness of this study. As mentioned earlier, these differences from theory (Eq. 2) are due to non-constant values.
of Z in the Z-Z\(_{DR}\) pairs, the different HCA classes that result in different relationships, and the Gaussian distribution of errors applied to the polarimetric bias addition. The theoretical curve is calculated using Eq. 2 and an approximation of average Z at each Z\(_{DR}\) point obtained by plotting Z versus Z\(_{DR}\) of the dataset and fitting a Gaussian curve. While there is a relatively high density of observations surrounding the theoretical curve, there is non-trivial spread about the curve in both directions. Only the negative errors are shown for simplicity. It is worth noting that some of the errors can exceed an order of magnitude difference between observation and theory.

B. R(A) vs. Z-Z\(_{DR}\)-R and Minimum Elevation Angle

The second example shows a comparison between the R(A) and Z-Z\(_{DR}\)-R methods in Fig. 3. R(A) generally shows higher rainfall estimates, especially in convection, as discussed in [11]. Although not shown, the R(A) method shows less spread about the gauge truths in this case, but generally runs too high compared with the Z-Z\(_{DR}\)-R method. Updates to the \(\alpha\) and R(A) relations are currently being studied to account for overestimates in convection, but the lack of dependence on polarimetric calibration will likely lead to the use of R(A) in the future. Due to this fact, the majority of this study moving forward will focus in the R(A) method and how these results change with parameters such as range to the target, elevation above ground level, and cross-azimuth resolution. An example that looks at the potential errors related to elevation above ground level is shown in Fig. 4. It should be noted that while the 0.5° R(A) data in Fig. 4 is similar to that shown in Fig. 3, it has been gridded and interpolated for fair comparison with upper elevations. This approach will drastically increase the number of data points in the eventual training of a regression model while maintaining a fair representation of QPE at each gauge site.

At the upper elevation, 1.5°, the stronger cores result in higher QPE values that push the errors toward 10 mm/hr. This is due to increasing Z and decreasing Z\(_{DR}\) with height in the core of the derecho east and north of the developing comma head. Although R(A) doesn’t depend on the absolute value of Z\(_{DR}\), \(\alpha\) does have a relation with Z\(_{DR}\) and the slope of Z/Z\(_{DR}\) is used to calculate an accurate \(\alpha\) value. At farther ranges, and thus higher elevations, the 1.5° scan begins entering the melting layer, resulting in the use of a Z-R relationship. This causes an underestimate of QPE in these areas. There is clearly a dependence on actual rainfall rate and position relative to the melting layer. These factors will be ingested as part of the regression model coming in the next stage of this work.

IV. DISCUSSION

The application of different error sources to WSR-88D QPE data shows how sensitive this type of estimate can be to radar calibration and network design. Given that SENSR is exploring various architectures, including but not limited to stationary phased arrays, rotating phased arrays, cylindrical arrays, dish antennas, and imaging arrays, radar calibration and performance is still an open question for the program. Calibration of the existing WSR-88D network has proven to be difficult, and it has been repeatedly observed that polarimetric calibration on planar arrays can be even more challenging. Although the preliminary performance requirements state a high level of polarimetric accuracy, understanding the tradeoffs of these errors versus cost and complexity will be invaluable to the SENSR effort. This is also important in understanding the potential utilization of a specific attenuation method for QPE. Each of these tradeoff examples can be used to model networks with varying density and single-site performance metrics. It should be clear to the reader that we are remaining system and network agnostic; no assumptions are being made about what SENSR will eventually result in. The purpose of this study is to evaluate all possible options.

The future of this effort is combining a significant number of observations into a regression model to predict not only data degradation, but also potential for data improvement as these variables are changed. By collecting a large number of cases...
spanning various precipitation types and scenarios and altering as many parameters as possible for each case, a substantial database can be built to train a model to predict errors based on network and system design. This tool will be useful for cost-benefit analysis in the SENSР effort.

V. CONCLUSIONS

This paper has presented preliminary results of a SENSР-based study for analyzing cost-benefit between network density and polarimetric bias with respect to QPE. The SENSР initiative does not assume any particular network or system design, leaving a wide range of options on the table for a future network. The ability to measure the associated tradeoffs of QPE, one of the most critical aspects of weather radar, will allow for an informative tool to aid in design decisions. This tool will be built using regression-based models based on large datasets collected from existing WSR-88D cases. Future work will involve the use of rain gauge data in order to determine absolute error with ground truth. While volumetric data can be used on a large scale to build extensive datasets, individual ground points will provide additional insight to the problem at hand. Aside from providing a network-based tool for SENSР, an extensive data assimilation and numerical weather prediction (NWP) modeling effort is anticipated using these datasets to assess the performance of NSSL’s prototype Warn-on-Forecast (WoF) system [15]. Any differences in radar coverage, particularly at low altitudes, will heavily impact the WoF performance.

ACKNOWLEDGMENT

The authors thank Dave Smalley, Betty Bennett, and Mike Donovan for their assistance developing the ORPG simulator. Mark Weber and Jud Stailey were instrumental in the design and planning of this study.

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