ABSTRACT  Measurement and response decoding is an ongoing challenge in the chipless radio-frequency identification (RFID) field. Measurement uncertainties, including tag/reader misalignment, radar cross-section or S-parameter error, and clutter, can cause response distortions, such as magnitude changes and resonant frequency shifts. These response distortions can lead to the improper assignment of a binary code or sensing parameter (i.e., improper decoding). This work aims to use local sensitivity analysis and Monte Carlo simulation to fully characterize the effects of misalignment, response parameter measurement error (e.g., vector network analyzer S-parameter error), and clutter on chipless RFID tag responses. From this type of comprehensive characterization, conclusions are drawn about the identification (ID) and sensing capabilities of the tags. In this work, the simulations are performed for two specific tags and the results are then corroborated with measurements of one of the tags. While the work is done for a near-field monostatic measurement setup, it is presented such that the same procedures can be applied to other tags and measurement setups, including far-field scenarios. Thus, a novel comprehensive tag performance assessment framework is provided. This work is divided into two parts. In Part I, the effects of tag/reader misalignment uncertainty are examined in depth through both simulations and measurements.
contributes to measurement error) that can each overwhelm or alter the tag response [3], [4]. The effects of tag/reader misalignment have been explored to varying extents. For example, Terranova et al. [5] considered the x-axis and y-axis translations (in plane) of the tag relative to the reader antenna (i.e., open-ended waveguide) when the tag is loading the waveguide (i.e., no standoff); Brinker et al. [6], [7] examined x-axis, y-axis, and z-axis translations (in plane and out of plane) of the tag relative to a waveguide; Gao et al. [8] considered 3° tilts of tags about each axis; Khadka et al. [9] investigated the effect of moving the tag up and down and changing the tag distance from bistatic horn antennas; Alencar et al. [10], [11] looked at misalignments in 1-cm steps over a 30 × 30 × 30 cm reading volume; and Kalansuriya et al. [12] examined yaw-based tilts up to 45°. Through these examples, it can be seen that tag/reader misalignments can cause magnitude changes, response shape distortions, and resonant frequency shifts, all of which can lead to improper decoding of the tag response depending on the coding method used. While these response changes may be tolerable in identification (ID) applications depending on the coding method used, they are often not acceptable in sensing applications where changes in resonant frequency or response shape are used to determine a sensing parameter [4], [13]. It should be noted that attempts have been made to mitigate the effects of tag/reader misalignment from both the tag perspective [14], [15], [16], [17] and reader perspective [18], [19], [20], [21]. However, each has its own limitations. Additionally, the effects of misalignments on decoding capabilities have yet to be fully characterized.

Other measurement uncertainties that can affect decoding performance are measurement parameter (e.g., RCS or S-Parameter) uncertainty and clutter. For the measurements in this work, a vector network analyzer (VNA) with a monostatic measurement setup is used; therefore, the complex S11 reflection coefficient uncertainty is considered here. Clutter (i.e., unwanted background reflections) can result from the environment in which the tag resides. When the environment is relatively static, coherent subtraction of the background response can be an effective approach to remove clutter. However, this process is not very effective when the environment is dynamic or when the tag is measured at a small reading distance [4], [8]. As such, it is beneficial to quantify the effects of clutter on the decoding performance of a tag through an approach that can be adjusted for different measurement configurations. On the other hand, reflection coefficient (S11) uncertainty is a function of the reader hardware, frequency range, IF bandwidth, averaging, cables, connectors, and the calibration procedure used [22], [23].

In regard to quantifying the effects of these measurement uncertainties, Monte Carlo simulations have been conducted that individually examine the effect of noise and clutter on the ability to decode a response and on the ability to determine the rotation angle of a rotation sensor [24], [25], [26]. However, to the best of the authors knowledge, Monte Carlo simulation has not been used to examine the effects of tag/reader misalignment or to quantify the effects of multiple chipless RFID measurement uncertainties occurring simultaneously.

Since misalignments, clutter, and S11 error are all measurement uncertainties that can affect decoding performance, this work aims to quantify the effects of all of these factors (both individually and in combination with each other) using local sensitivity analysis and Monte Carlo simulation. For this purpose, two different tag designs and two different coding methods with different coding parameters are considered here. Multiple tag designs and coding methods are used in order to more comprehensively examine the effects of measurement uncertainty on chipless RFID system performance and to provide insight into how the proposed framework can be used to perform system optimization.

Probabilistic distributions are used to describe the misalignment-based measurement uncertainties. The effects of discretization on Monte Carlo simulation performance are also examined. The simulation results are verified through measurement, and performance across simulation and measurement is evaluated in terms of metrics, such as detection error rate (DER), bit-error ratio (BER), resonant frequency shift, local sensitivity, root-mean-square error (RMSE), and bit differences. In performing this work, a novel framework is provided for evaluating the effects of measurement uncertainty on chipless RFID tag performance that can be applied to other tag designs and measurement setups used for both identification and sensing applications. Overall, the novelty of this work can be summarized as follows.

1) The use of local sensitivity analysis and Monte Carlo simulation to comprehensively examine the effects of tag/reader misalignment.
2) The examination of the effects of S11 error and clutter on tag performance through Monte Carlo simulation.
3) The use of Monte Carlo simulation to evaluate the effects of multiple chipless RFID measurement uncertainties simultaneously. This evaluation is done in terms of both identification and sensing applications (i.e., the likelihood of bit differences and the achievable sensing resolution based on the resonant frequency distribution).
4) The development of a framework for assessing the effects of chipless RFID measurement uncertainties that can be applied to different tags and measurement setups.

This work is divided into two parts. In this part, Part I, the effect of tag/reader misalignment uncertainty is examined in depth through both simulation and measurement. In Part II, the effects of S-parameter error, clutter-based uncertainty, and the combination of these uncertainties with misalignment uncertainty are investigated. An example of the application of this tag performance assessment framework is also provided in Part II [27].
In this article (Part I), Section II presents the tags and coding methods that are used in the analysis that is central to this work. Section III contains the local sensitivity analysis that was conducted, which provides insight into how misalignments effect tag responses and into which misalignments are the most important to control for during measurement. Section III also describes the likelihood of different misalignments and combinations of misalignments as determined through a Monte Carlo simulation. In Section IV, another Monte Carlo simulation was conducted to examine the effect of misalignment on tag responses both in terms of decoding metrics (i.e., BER, DER, and Throughput) and the resonant frequency distribution. Finally, Section V provides measurements to corroborate the simulation results presented throughout this article (Part I).

II. TAG DESIGNS AND CODING METHODS

A. CHIPLESS RFID TAG DESIGNS

Two relatively simple tags are considered in this work, namely: 1) a circular patch tag and 2) a 4C tag. Both tags contain a ground plane which helps minimize response detuning caused by the object or structure to which the tag is attached [9]. The circular patch tag is based on the designs described in [6], while the 4C tag design comes from the study in [28]. The circular patch was chosen due to its simplicity and symmetry, which reduces the number of simulations needed to characterize its behavior under misalignment conditions (i.e., a translation in the +X-direction will produce the same response as an equal translation in the −X-direction). The 4C tag is not symmetric, but still only possesses one primary notch in its frequency response and one that is just outside the frequency range considered (i.e., 12.5 GHz). This second notch can shift into the considered frequency range under certain misalignment and environmental conditions, causing drastic binary code changes, especially when using coding methods like the one proposed in [29]. This lack of symmetry and possibility for changing the number of notches in the response allow for evaluating the subsequent measurement uncertainty characterization procedures with a more complex tag in an incremental manner. The CST Studio Suite models of these tags and their simulated S_{11} (complex reflection coefficient) responses are shown in Fig. 1. Both tags shown in Fig. 1(b) and (c) were designed to operate at X-band (8.2–12.4 GHz) where the wavelength in air varies from 36.6 to 24.2 mm, and were designed to be measured in the near-field of an open-ended rectangular waveguide with an engineered flange [see Fig. 1(a)] [30]. As such, a setup involving a 10-mm standoff and an X-band waveguide with an engineered flange was used to produce the simulation results shown in Fig. 1. Having the tag placed at the center of the waveguide aperture at a distance of 10 mm is considered to be the “aligned” reference case. Here, the coordinate system is defined with the center of the face of the tag being the origin and the z-axis is normal to the face of the tag. By examining the two responses in Fig. 1(d), it can be seen that the notch in the patch tag response has a larger resonant depth and more bandwidth than that of the 4C tag response. This relationship between the resonant depth and bandwidth was also observed in [31].

As previously mentioned, misalignments (both translations and rotations) can cause response distortions, including changes in magnitude and resonant frequency shifts. Fig. 2 shows some of the simulated responses of both tags under different misalignment scenarios for illustration purposes. In Fig. 2, dx corresponds to a translation along the x-axis and xrot corresponds to a rotation about the x-axis. The other designations, namely, dy, dz, yrot, and zrot, have been made accordingly. For all the cases considered in Fig. 2, only one variable is changed at a time. It should also be noted that for brevity, only one misalignment case of each type (dx, dy, dz, xrot, yrot, and zrot) is shown for each tag. Fig. 2(a) shows that z-axis translations (i.e., moving the tag closer or further from the waveguide aperture) cause the largest change in resonant frequency and resonant depth for the cases considered for the patch tag. Fig. 2(b) additionally shows changes
in the 4C tag response shape on both sides of the resonance. These changes can be captured by some coding methods and can also be examined through the perspective of calculating the RMSE between the response and a reference (e.g., the aligned case). In comparing Fig. 2(a) and (b), the relationship between tag geometry/polarization behavior and the tag response can also be examined. Overall, depending on the coding method used, these response changes due to misalignment may or may not create bit differences. As such, both code-based metrics (i.e., bit differences, BER, DER, and throughput) and response characteristic-based metrics (i.e., RMSE and resonant frequency shift) can be used to quantify the consequences of misalignment, as will be demonstrated throughout this article [4].

While manufacturing errors in tags (e.g., improperly dimensioned resonators or tolerances in the complex permittivity of substrates) can also cause unexpected changes in the response, they are not a subject of study in this work [8], [14]. The reason for this is that these manufacturing errors are constant from one measurement to the next so they are not considered to be measurement uncertainties.

**B. CODING METHODS AND METRICS**

As previously mentioned, a binary code can be assigned to a tag response in a number of different ways [4], [13]. For this work, multiple configurations of two different coding methods with different sensitivities to response shape changes are utilized to examine the role the coding method plays in tag performance. The two coding methods are illustrated in Fig. 3. The first coding method considered (subsequently referred to as Method 1) establishes a threshold after the response has been normalized, divides the response into windows, and then assigns 1s and 0s based on whether the response is primarily above or below the threshold in each window as determined by integration (see Fig. 3) [4], [13], [29]. For this work, two different window widths (80 MHz and 170 MHz) and three different thresholds (−1, −3, and −5 dB) are considered for this method. Coding via Method 1 with the six combinations of these parameters will provide insight into how these parameters can be optimized to maximize tag performance for a given application [6], [13], [29]. In general, a smaller window width results in smaller response shape changes being translated into bit differences in the code (i.e., higher sensitivity) at the expense of generating longer codes. In other words, codes generated with larger window widths using Method 1 can be more robust to measurement uncertainty, which is often desirable in identification applications. This relationship will be examined in the subsequent sections. Given a coding bandwidth that covers X-band (8.2–12.4 GHz), using a window width of 80 MHz results in a 52-bit long code while using a window width of 170 MHz results in a 25-bit code.

The second coding method considered (subsequently referred to as Method 2) is a more “traditional” method where the presence of a notch in the response results in a 1 in the code and the absence of that notch results in a 0 in the code (see Fig. 3). Thresholds of −1, −5, −10, and −15 dB are considered, and in order for a notch to be considered present the normalized response must cross the threshold on both sides of the resonant frequency. Method 2 is geared toward identification applications where there is often an expected number of notches to be detected. It should be noted that Method 2, is not well suited for sensing applications where changes in the response, such as resonant frequency shift, are often correlated to the sensing parameter of interest [4]. In Fig. 3, both coding methods are employed for the patch tag reference response (no misalignment) after normalization given a threshold of −5 dB.
A window width of 170 MHz is used in the illustration of Method 1. As can be seen, Method 1 results in a 25-bit code of [000111111110000000011111] while Method 2 results in a 1-bit code of [1], due to there only being one notch in the response. It should be noted that the notch is considered present for Method 2 in Fig. 3 because the response crosses the −5-dB threshold on both sides of the resonant frequency (10.38 GHz) at 10.01 and 11.72 GHz.

For both coding methods, different coding-based metrics, namely, BER, DER, and Throughput, can be calculated as follows [4]:

\[
\text{BER} = \frac{\text{number of bit differences}}{\text{length of code}}
\]

\[
\text{DER} = \frac{\text{number of failed decodings}}{\text{number of attempted decodings}}
\]

\[
\text{Throughput} = 1 - \text{DER}.
\]

It should be noted that the BER can be calculated for a single instance of decoding (i.e., 1 trial) or the average BER can be calculated over many trials as is subsequently done for the Monte Carlo simulations. From the definitions of BER, DER, and throughput above, it can be seen that BER describes the error rate on a bit-by-bit basis for a single decoding attempt, while DER and throughput describe how frequently a response is decoded correctly in its entirety when many decoding attempts are considered. Overall, it is desirable to have a low BER and DER and a high throughput. It is important to note that these metrics vary widely based on the tag, measurement setup, coding method, and the strictness of the criteria for claiming successful decoding. Therefore, it is often difficult to make direct comparisons of chipless RFID system performance across different works [4], [26], [32]. This is discussed more in depth in [4].

III. LOCAL SENSITIVITY ANALYSIS

Local sensitivity analysis is aimed at looking at the effects of individual parameters on the response of a tag [33]. In the case of chipless RFID measurement, the effects of different types of misalignments can be separately examined to provide insight into how the tag response changes under different measurement conditions. Additionally, local sensitivity analysis can provide insight into the type of misalignment that is the most important to control during a measurement. In order to perform this analysis, probability distributions, representing each misalignment-based measurement uncertainty, were developed and then the changes in the tag’s code, resonant frequency, and RMSE were examined for misalignment values falling in the 95% confidence intervals of the distributions.

A. SELECTED DISTRIBUTIONS AND INITIAL MONTE CARLO SIMULATIONS

Each uncertainty under consideration can be described by a probabilistic distribution. The distributions were developed through the expert solicitation process, as described in [34], due to the impracticality of quantifying the misalignments that occur during the actual measurement process. For both rotation- and translation-based misalignments about the \(x\)-, \(y\)-, and \(z\)-axes, normal distributions were selected. This is representative since the person making the measurement is just as likely to have tag/reader misalignment in the +\(X\)-direction as the −\(X\)-direction, and similarly for all other types of misalignments considered. It should be noted that all misalignment-based probabilities are considered to be independent of each other (e.g., a \(dx\) translation does not influence the probability of there being a \(xrot\) rotation). The distributions for translations and rotations about all three axes are shown in Fig. 4. The histograms of the distributions were created by generating 100,000 random variables using the distribution parameters and plotting them. This step can be considered as part of the Monte Carlo simulations being conducted for this work. While the translations along the \(x\)-, \(y\)-, and \(z\)-axes all have the same distribution, the distributions for rotations about the \(x\)- and \(y\)-axes differ from that of \(z\)-axis rotations. This is also described in Table 1. In Table 1, \(\mu\) represents the mean and \(\sigma\) represents the standard deviation associated with these distributions. For normal distributions the 95% confidence interval is defined by bounds at \(\mu \pm 2\sigma\).

While the distributions presented in Fig. 4 are continuous, mimicking real life (i.e., real misalignments would not occur only as discrete positions), it is impractical to characterize the sensitivity of the tag response to measurement uncertainties on a continuous scale due to limited precision in measurement equipment. Additionally, in the case of local sensitivity analysis where the tag response is evaluated under different misalignment conditions over a range of values, only a finite number of cases can be evaluated. Thus, the distributions were discretized along multiple intervals to determine the acceptable discretization. As such, discretizations of 0.1, 0.5, and 1 were selected for both rotations and translations with the units for rotations in \(\text{mm}\).
TABLE 1. Descriptions of misalignment distributions.

| Measurement Uncertainty | Distribution Description | 95% Confidence Interval |
|-------------------------|--------------------------|------------------------|
| X-Position              | Normal: µ=0, σ=0.9        | -1.80                  |
| Y-Position              | Normal: µ=0, σ=0.9        | 1.80                   |
| Z-Position              | Normal: µ=0, σ=0.9        | -1.80                  |
| X-Rotation (Pitch)     | Normal: µ=0, σ=2.8        | -5.60                  |
| Y-Rotation (Yaw)        | Normal: µ=0, σ=2.8        | -5.60                  |
| Z-Rotation (Roll)       | Normal: µ=0, σ=3.5        | -6.99                  |

FIGURE 5. Flowchart for the Monte Carlo simulation process used to generate misalignment risk curves.

- Assign distributions for uncertainties
- Generate random variable for each uncertainty [dx, dy, dz, xrot, yrot, zrot]
- Discretize set of uncertainties
- Store max of [dx, dy, dz]
- Store max of [xrot, yrot, zrot]
- Calculate risk curves

- If i ≤ trials

FIGURE 6. Risk curves for misalignments: (a) risk curves for each of the six misalignments considered, (b) effect of discretization on the risk curves for three misalignment parameters, (c) risk curves for combinations of misalignments, and (d) effect of discretization on the risk curves for combinations of misalignments.

- dx
- dy
- dz
- xrot
- yrot
- zrot

- dx: Discretization=0.5
- xrot: Discretization=0.5
- yrot: Discretization=0.5
- dx: Discretization=1
- xrot: Discretization=1
- yrot: Discretization=1

- Translation
- Rotation
- AI

- Translation: Discretization=0.1
- Rotation: Discretization=0.1
- AI: Discretization=0.5
- Translation: Discretization=0.5
- Rotation: Discretization=1
- AI: Discretization=1

degrees and the units for translations being in millimeters.

A discretization of 0.1 means that each misalignment was rounded to the nearest 0.1, while 0.5 means that each misalignment was rounded to the nearest 0.5, and 1 means that each misalignment was rounded to the nearest integer. No discretization value means that the misalignment value was not rounded and was instead allowed to maintain its double-precision floating-point value, which is the default precision in MATLAB.

Based on the distributions and defined discretization schemes, the probability of there being a misalignment can be calculated using Monte Carlo simulation. The flowchart of the process for the Monte Carlo simulation is shown in Fig. 5. Fig. 6 shows the risk curves for different misalignments and combinations of misalignments when 100,000 trials are considered. Risk curves can be interpreted as the probability of exceeding a given x-axis value. For example, Fig. 6(a) shows that there is an approximately 5% chance of having a dx, dy, or dz translation greater than 2 mm.

In Fig. 6(b), the effect of discretization can be seen for dx, xrot, and zrot. These three misalignments were selected for illustration purposes due to all three translations (dx, dy, and dz) creating the same risk curve, and xrot and yrot creating the same risk curve, as shown in Fig. 6(a). In Fig. 6(b), four different discretizations are shown. The no discretization case is referred to as the continuous risk curve. As expected, as the discretization value increases, the risk curve deviation from the continuous risk curve also increases. The same is true for the risk curves of combinations of misalignments, which are shown in Fig. 6(c) and (d). In these two figures, an x-axis value of three means that all misalignments of that type are three (mm or degrees) or less. In other words, the x-axis depicts the maximum misalignment magnitude of a generated
set of misalignments, where translations and rotations are first considered separately and then together. Fig. 6(c) and (d) shows that for a given misalignment magnitude there is a higher probability of a rotation-based misalignment being present at a value that is at least that magnitude than there is for a translation-based misalignment. For example, for the case in Fig. 6(c) where all misalignments are less than or equal to two (mm or degrees), there is a 7.5% chance of at least one translation type \((dx, dy, \text{ or } dz)\) having a magnitude greater than 2 mm, while there is an 88.1% chance of at least one rotation type \((xrot, yrot, \text{ or } zrot)\) having a magnitude greater than 2°. When translation and rotations are considered together, the probability of exceedance increases slightly above that of just rotations for small magnitudes but then follows the rotation curve closely. Another takeaway from this Monte Carlo simulation and the associated risk curves in Fig. 6 is that it is very unlikely that there will be perfect tag/reader alignment during measurement (0% for the continuous case, 0% for a discretization of 0.1, 0.003% for a discretization of 0.5, and 0.02% for a discretization of 1). Therefore, quantifying the effects and sensitivity of the tag response to misalignment becomes an important issue of interest.

B. LOCAL SENSITIVITY ANALYSIS

The local sensitivity was calculated in terms of resonant frequency, resonant frequency shift, RMSE, and bit differences over a range of values for each misalignment type. Due to limitations in the precision of the measurement equipment used, a discretization scheme of 0.5 for translations and 1 for rotations was selected for subsequent use throughout this work. This choice is also supported by the risk curves in the previous section which showed that rotation-based misalignments are more tolerant to discretization than translation-based misalignments (i.e., the discretized rotation-based risk curves follow the continuous curve more closely than the discretized translation-based risk curves do).

The selected discretization scheme is indicated in Table 2 in the ranges shown below each parameter name. The syntax can be parsed as start value: step size: stop value. The start and stop values were determined by rounding the 95% confidence interval bounds in Table 1 to the nearest integer. The sensitivity was calculated according to

\[
\text{Sensitivity} = \frac{\text{number of bit differences}}{|\text{misalignment}|}. \tag{4}
\]

In (4), the number of bit differences is determined by comparing the code generated for a response with a certain misalignment to the code for the reference case (perfectly aligned). This means that for the case of \(-2\) mm of \(dx\) translation using Method 1 with coding parameters of a threshold of \(-3\) dB and a 170-MHz window width that results in a 25-bit long code, the sensitivity was calculated as 0.5 (1-bit difference divided by a misalignment magnitude of 2). To generate the values in Table 2, the finite sensitivities over each misalignment range were averaged for each of the six combinations of Method 1 coding parameters (see Fig. 3). The cells that produce the lowest sensitivity for each type of misalignment were highlighted in green and all sensitivities for a type of misalignment were averaged to produce the entries in the rightmost column of Table 2. It should be noted that only the configurations of coding Method 1 were reported in Table 2 due to there being only one resonance in each tag’s response resulting in 1-bit long codes when using Method 2 (see Fig. 3), which does not provide enough variability to calculate meaningful code-based local sensitivities. However, Method 2 is used in the subsequent Monte Carlo simulations that are discussed in Section IV. By examining the number of green highlighted cells in each column, we can gain an insight into the manner by which the coding method can be optimized, in terms of the threshold and window width, to produce the lowest sensitivity to misalignment. For the coding configurations considered, a threshold of \(-1\) dB and a window width of either 80 or 170 MHz would produce codes that are the most robust against individual misalignments for the patch tag. On the other hand, a threshold of \(-5\) dB with a window width of 170 MHz would produce codes that are the most robust against individual misalignments for the 4C tag.

| Parameter | Average Sensitivity: Coding Method 1 (bits per increment of misalignment) | Average Sensitivity Across Coding Method Configs. |
|-----------|-------------------------------------------------|-----------------|
| Code Length (bits) | 25 | 52 |
| Threshold (dB) | -1 | -3 | -5 | -1 | -3 | -5 |
| Circular Patch Tag | | | | | | |
| \(dx\) | 0.00 | 0.06 | 0.42 | 0.13 | 0.13 | 1.63 | 0.39 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| \(dy\) | 0.13 | 0.29 | 0.75 | 0.00 | 0.04 | 2.22 | 1.63 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| \(dz\) | 2.21 | 4.38 | 7.33 | 2.20 | 4.38 | 7.33 | 1.69 | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) | (0.08) |
| \(xrot\) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| \(yrot\) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| \(zrot\) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

4C Tag

| Parameter | Average Sensitivity: Coding Method 1 (bits per increment of misalignment) | Average Sensitivity Across Coding Method Configs. |
|-----------|-------------------------------------------------|-----------------|
| Code Length (bits) | 25 | 52 |
| Threshold (dB) | -1 | -3 | -5 | -1 | -3 | -5 |
| Circular Patch Tag | | | | | | |
| \(dx\) | 0.00 | 0.27 | 0.13 | 0.00 | 0.00 | 0.00 | 0.00 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| \(dy\) | 0.00 | 0.13 | 0.29 | 0.00 | 0.00 | 0.00 | 0.00 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| \(dz\) | 0.00 | 0.17 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| \(xrot\) | 0.12 | 0.13 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| \(yrot\) | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| \(zrot\) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
FIGURE 7. Resonant frequency sensitivity to misalignments: (a) patch tag resonant frequency sensitivity to misalignments and (b) 4C tag resonant frequency sensitivity to misalignments.

the rotational symmetry of the tag design followed by y-axis rotation. For the 4C tag, x-axis rotation and z-axis rotation produced the lowest sensitivities. Similar trends of sensitivity can also be seen in the average RMSE, average resonant frequency, and average resonant frequency shift over each misalignment type range that are reported in Table 3 and the resonant frequency variation that is depicted in Fig. 7 for both tags. In Table 3, the RMSE was calculated as follows:

$$\text{RMSE} = 20\log_{10} \left( \sqrt{\frac{1}{f} \sum_{i=1}^{f} (S_{11\text{ref}} - S_{11\text{mis}})^2} \right). \quad (5)$$

In (5), $f$ represents the number of frequency points in the tag’s $S_{11}$ response and for each misalignment case, the response under misalignment is subtracted coherently from the reference response with both $S_{11\text{ref}}$ and $S_{11\text{mis}}$ in linear complex form. RMSE is calculated in dB so that it can be compared to the measurement accuracy of the reader (i.e., a VNA in this case). In examining Fig. 7, it can be seen that for both tags, the resonant frequency is the most sensitive to $dz$ translations. However, when the patch tag is compared to the 4C tag through Table 3 and Fig. 7 [note the difference in the y-axis scales between Fig. 7(a) and (b)], it can be seen that the patch tag has greater variability in the resonant frequency for each translation-based misalignment type.

In comparing Tables 3 to 2, Table 3 describes slightly different trends for the 4C tag. Table 3 shows that the 4C tag responses were the most similar to the reference case response for z-axis rotation based on the low RMSE, and also had the smallest average resonant frequency shift for z-axis rotation. These differences demonstrate how code-based sensitivity alone, may not comprehensively describe how the tag response reacts to misalignment. It also demonstrates the (subjective) dependency of the code-based sensitivity on the coding method selected.

As previously mentioned, the RMSE can also be evaluated in terms of the measurement accuracy of the reader being used. For reflection-based measurements, the $S_{11}$ uncertainty is dominated by the residual directivity of the VNA after calibration, which is influenced by the quality of the calibration kit used. For the VNA used in the measurement setup (Anritsu MS46131A-043) in this work, the directivity for a mechanical connector-based calibration kit is reported to be between 42 and 36 dB over the considered frequency range of (8.2–12.4 GHz). This means that responses with RMSEs less than $-30$ dB are on the order of the measurement accuracy of the system and would be difficult to distinguish from the reference case in practice (i.e., the $S_{11}$ uncertainty could be greater than the difference between the two responses as expressed through RMSE) \[35\], \[36\]. $S_{11}$ uncertainty is investigated in more detail in Part II.

### IV. MONTE CARLO SIMULATION

By examining the effects of different measurement uncertainties on a chipless RFID tag’s response, conclusions can be made about the consequences of such uncertainties. These results can also be used to enable the person making the measurements to make informed decisions as to the manner by which the measurements should be conducted (e.g., choosing whether or not to calibrate the VNA used to make the measurements).
measurements). Misalignment-based uncertainty is examined here in Part I, while $S_{11}$ and clutter-based uncertainty are examined in Part II.

**A. MISALIGNMENT UNCERTAINTY**

In the previous section, the local sensitivity of a tag response to misalignments of a single type was investigated. However, in practice, multiple misalignments can occur simultaneously, which can exacerbate the response changes seen in Fig. 2. Thus, Monte Carlo simulation can again be employed to assess the consequences of having multiple misalignments during measurement. For this, the probability distributions for each misalignment shown in Fig. 4 were used with the selected discretization scheme (0.5 for translations and 1 for rotations) to generate a misalignment scenario that was then simulated in CST Studio Suite. Each simulated response was then coded using each configuration of Methods 1 and 2 (see Fig. 3) and the codes were compared to that of the reference response (no misalignment). The process for this Monte Carlo simulation is depicted in the flowchart in Fig. 8. For this Monte Carlo simulation, 100,000 trials were not used due to the time required to simulate each misalignment scenario. Instead, simulations were run until the cumulative distribution function (CDF) of the number of bit differences converged. In the end, 1100 cases were used to generate the CDF in Fig. 9 and calculate the decoding metrics in Table 4. The same 1100 cases were used for each coding method in order to compare them more consistently, since there was not a large number of trials to average out outliers.

In the legend in Fig. 9, $t$ represents the threshold used in the coding method, while $n$ represents the number of bits in the code. Each curve in Fig. 9 has a discretized nature due to the number of bit differences being an integer (i.e., fractional bit differences are not possible) and each curve describes the probability of having a certain number of bit differences or fewer. For example, Fig. 9(a) shows that for the Patch tag when Method 1 is used for coding with a threshold of $-3$ dB and a 52-bit code length there is a 51.73% chance of having two or fewer bit differences. Fig. 9(b), on the other hand, shows that there is a 67.91% chance of having no bit differences when a threshold of $-5$ dB is used.

In comparing coding methods 1 and 2 for each tag (Fig. 9(a) versus (b) and Fig. 9(c) versus (d)), it can be seen that different coding methods and coding method parameters each result in a different probability of bit differences. In comparing the patch tag to the 4C tag through Fig. 9, it can be seen that the patch tag tends to be more susceptible to bit errors due to misalignment-based uncertainty across both coding methods than the 4C tag. This is despite the 4C tag generally having greater average local sensitivity across coding methods to individual misalignments and the patch tag being insensitive to $z$-axis rotations. This demonstrates the importance of considering multiple misalignments simultaneously through a Monte Carlo analysis, as a local sensitivity analysis cannot comprehensively capture the consequences of misalignment. Rather, local sensitivity analysis can primarily indicate which type of misalignment is the most critical to control for in the measurement setup.

From these results depicted in Fig. 9, the BER per trial, the average BER for all 100,000 trials, DER, and throughput can also be calculated, which are reported in Table 4. As discussed in [4], decoding performance is affected by the tag design, the measurement setup, and the decoding method. Thus, it is expected that the same coding method should produce different metrics for different tags. This is confirmed by the results in Table 1 which generally show

![FIGURE 8. Flowchart for misalignment uncertainty Monte Carlo simulation.](image-url)
FIGURE 9. Cumulative probability distribution of bit differences when misalignment uncertainty is considered with different coding methods: (a) CDFs for patch tag with coding method 1, (b) CDFs for patch tag with coding method 2, (c) CDFs for 4C tag with coding method 1, and (d) CDFs for 4C tag with coding method 2.

FIGURE 10. Simulated resonant frequency distribution due to misalignment-based uncertainty: (a) patch tag and (b) 4C tag.

TABLE 5. Resonant frequency distributions.

| Tag | Ref. Resonant Frequency (GHz) | Average Resonant Frequency (GHz) | 95% CI (GHz) |
|-----|--------------------------------|----------------------------------|-------------|
| Patch | 10.3840 | 10.3815 | 9.9277 | 10.8353 |
| 4C | 11.2030 | 11.1927 | 11.1766 | 11.2088 |

mean that the threshold is set in such a way that response changes are not being captured in the code. Whether this is a benefit or not is dependent on the application. These metrics will subsequently be used to compare the effects of other measurement uncertainties on the decoding of tag responses.

These effects can also be examined through the resonant frequency distribution (i.e., the histogram of the resonant frequency) by recording the resonant frequency at the code assignment step of the process outlined in the flowchart Fig. 8. The resonant frequency distribution for both tags is depicted in Fig. 10. It is worth noting that the resonance frequency is not coding-method dependent, so only one set of results is provided for each tag. As can be seen, when multiple misalignments are considered, the resulting resonant frequency tends to shift relative to the aligned case. It can also be seen that the resonant frequency spread is wider for the patch tag than the 4C tag, which is likely due to the higher $dz$ sensitivity of the patch tag. This is also depicted in Table 5. Table 5 compares the resonant frequency for the aligned case, with the average resonant frequency and 95% confidence interval of the resonant frequency distributions when multiple misalignments are considered simultaneously through Monte Carlo simulation. From Table 5, it can be seen that for both tags, the average resonant frequency, when...
misalignments are considered, tends to be slightly lower than the reference case. This indicates that misalignments tend to shift the resonant frequency down more often than up. This information is useful in sensing applications where it can be important to determine how likely a resonant is to shift out of the operating frequency range, which can affect the sensing range (e.g., in embedded materials characterization) [29].

V. MEASUREMENT

In order to corroborate the simulation results for the resonant frequency distribution in the previous section, a set of measurements was conducted with the 4C tag. The fabricated tag and measurement setup are shown in Fig. 11. The measurement setup consists of a calibrated VNA connected to an X-band (8.2–12.4 GHz) rectangular waveguide with an engineered flange held in a vice such that the aperture of the waveguide is radiating into air. The tag was adhered to a piece of low permittivity green foam using double stick tape and then aligned to the best ability of the person making the measurement with the waveguide and the $S_{11}$ response was measured. The aligned case here is the same as the reference case used previously (10-mm standoff with the tag centered on the waveguide aperture). In between each measurement, the tag was removed from the foam, re-adered, and realigned in order to capture the variability that comes from unintentional misalignment during measurement. In this experiment, a total of 550 measurements were conducted among three different people to capture the human error of different measurement takers. In this way, the reasonableness of the selected distributions (see Fig. 4) and the expected variability in the resonant frequency due to misalignment could be examined.

Fig. 12 shows 20 randomly-selected $S_{11}$ measurements out of the set of 550 measurements and the resonant frequency distribution that results from all 550 measurements. In comparing it to the distribution shown in Fig. 10(b) for the 4C tag, it can be seen that the average resonant frequency ($\mu$) is slightly lower in measurement than it is in simulation. This is likely due to manufacturing error since the error is consistent throughout the measurements [6], [14]. It can also be noted that the standard deviation of the measurements is larger than that for the simulations. This difference can be attributed to the fact that in the measurements $S_{11}$ uncertainty and clutter-based uncertainty are also present in addition to the misalignment-based uncertainty, while in the simulations presented so far only misalignment-based uncertainty was considered. For this reason, the effects of $S_{11}$ uncertainty and clutter-based uncertainty are investigated individually and in conjunction with misalignment-based uncertainty in Part II of this work.

VI. CONCLUSION

This work comprehensively examined the effects of misalignment on chipless RFID tag performance through both local sensitivity analysis and Monte Carlo simulation using two tags and multiple coding methods. Probabilistic distributions were proposed to describe the likelihood of different types of misalignments and the probability of individual misalignments and combinations of misalignments was presented. Local sensitivity analysis was then performed to examine the effects of individual misalignments on tag performance and assess which types of misalignments are the most important to control for during measurement. The sensitivity, average RMSE, average resonant frequency, and average resonant frequency shift were reported for different types of misalignment and different coding method configurations. This analysis showed that $dz$ translations are the most important type of individual misalignment to control for in the measurement setup for both tags considered. The local sensitivity analysis also affirmed that using larger window widths (i.e., 170 MHz) tends to produce codes that are more resistant to misalignments. To extend this analysis into more
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