Meta-material Sensors based Internet of Things for 6G Communications

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Abstract—In the coming 6G communications, the internet of things (IoT) serves as a key enabler to collect environmental information and is expected to achieve ubiquitous deployment. However, it is challenging for traditional IoT sensors to meet this expectation because of their requirements of power supplies and frequent maintenance, which are due to their power-demanding sense and transmit modules. To address this challenge, we propose a meta-IoT sensing system, where the IoT sensors are based on specially designed meta-materials. The meta-IoT sensors achieve simultaneous sensing and transmission by physical reflection and require no power supplies. In order to design a meta-IoT sensing system with optimal sensing accuracy, we jointly consider the sensing and transmission of meta-IoT sensors and propose efficient algorithms to optimize the meta-IoT structure and the sensing function at the receiver. As an example, we apply the meta-IoT system to sensing environmental temperature and humidity levels. Simulation results show that by using the proposed algorithm, the sensing accuracy can be largely increased.

I. INTRODUCTION

For the next coming 6G communications, it is envisioned that the internet of things (IoT) lays the foundation for various important sensing applications [1]. To support sensing applications in intelligent industrial processing and environmental monitoring, an extremely large number of IoT sensors need to be spread pervasively in the environments to collect information. The number of IoT sensors needed in 6G is reckoned to be 10-fold more than that in 5G, reaching 10 million devices per square km [2]. In order to support the ultra-massive deployment, it is necessary for the IoT sensors in 6G to have extremely low power consumption, so that they can be energy-saving and used for continuous sensing without any human intervention or maintenance for an ultra-long time [1].

Nevertheless, it is challenging for existing IoT sensors to satisfy the demands of 6G. Because existing IoT sensors need energy suppliers, such as lithium batteries or energy harvesters, to support their power-consuming sensing, modulation, and transmission modules. Specifically, the power consumption and sophisticated microchips needed in the modulation of sensing results and transmission of the signals result in non-negligible costs and expenses, which make these IoT sensors not suitable for the ultra-massive deployment. To meet the demand for pervasive environment sensing in 6G, it is expected to develop sensors with simultaneous sensing and transmission, where sensing and transmission are performed simultaneously through physical signal reflection. By this means, no extra energy or sophisticated microchips are required.

Fortunately, meta-material sensors have shown the potential of simultaneous sensing and transmission for sensing applications in 6G communications [3], [4], which we refer to as the meta-IoT sensors. The meta-IoT sensors are printed circuits on supportive substrates combined with some sensitive materials, which together work as reflectors for wireless signals. Their working principle is that their reflection coefficients for wireless signals are sensitive to surrounding environmental conditions. Therefore, by analyzing the reflected signals from the meta-IoT sensors, the influence of the environmental conditions can be recognized, and the values of the environmental conditions can be estimated.

In literature, several works have discussed using meta-materials for sensing environmental conditions. In [3], the authors proposed a meta-material sensor which is composed of split-ring resonators (SRRs) and a temperature-sensitive polymer, which can be used to sense CO2 concentration or temperature. In [5], the authors proposed a meta-material temperature sensor with a double SRR, which can sense temperature levels in harsh high-temperature environments. In [6], the authors designed a humidity sensor based on a perfect meta-material absorber. Moreover, in [7], the authors utilized meta-materials to design an enhanced passive humidity sensor.

However, the above literature focuses on the design to improve the sensing performance while the transmission lacks joint consideration. As the design of meta-IoT sensors not only influences the sensing performance, but also has an impact on the signal transmission, it is important to design the meta-IoT sensor joint considering both sensing and transmission.

In this paper, we design a general meta-IoT sensing system, which is able to sense multiple environmental conditions. We jointly considering the influence of both sensing and transmission and formulate a joint meta-IoT structure and sensing function optimization problem, which is solved efficiently through problem decomposition. The simulation results verify the effectiveness of the proposed design to optimize the meta-IoT sensor design in terms of sensing accuracy.

The rest of the paper is organized as follows. In Section III, we introduce the proposed meta-IoT sensors. In Section III, we...
the model of the meta-IoT sensing system is described. In Section IV, we formulate a joint meta-IoT structure and sensing function optimization problem and propose the algorithm to solve it in Section V. Simulation results are provided in Section IV and a conclusion is drawn in Section VII.

II. META-IoT SENSORS

Meta-materials are artificial periodic structures exhibiting exotic properties, which are underpinned by their special frequency responses for wireless signals [8], [9]. By designing a meta-IoT sensor with specific structure and sensitive materials, we can make the frequency response of the meta-IoT sensor sensitive to various sensing targets, such as temperature, humidity, gas concentration, and so on.

As shown in Fig. 1 (a), the meta-IoT sensor consists of \( N_T \) meta-IoT units for \( N_T \) different target environmental conditions, which we refer to as \( N_T \) sensing target conditions. Each meta-IoT unit consists of a SRR with a horizontal gap printed on a supportive sensitive substrate. The substrate of the meta-IoT sensor is made of dielectric materials, and the SRR is made of metal. The detailed dimensions of a meta-IoT sensor are illustrated in Fig. 1 (a).

Each meta-IoT unit can be approximated by a RLC resonant circuit as shown in Fig. 1 (b). For the \( n \)-th meta-IoT unit with gap width \( d_n \), given the sensing target condition vector of the \( N_T \) sensing targets being \( c = (c_1, \ldots, c_{N_T}) \), the impedance of the circuit can be calculated as [1]

\[
Z_n(f, c, d_n) = \frac{1}{2\pi f L_{para,n}} + 2\pi f C_{para,n} + 2\pi f C_{gap,n}(d_n) + \frac{1}{R_{gap,n}(c, d_n)^{-1}}, \tag{1}
\]

where \( i \) denotes the imaginary unit, \( f \) denotes the frequency of incident signals on the meta-IoT unit, and \( L_{para,n} \) and \( C_{para,n} \) are the parasitic inductance and capacitance of the SRR, respectively. Besides, \( R_{gap,n}(c, d_n) \) and \( C_{gap,n}(d_n) \) can be modeled as

\[
R_{gap,n}(c, d_n) = \frac{d_n}{\rho_{mat,n}(c) W_{SRR} H_{SRR}}, \quad C_{gap,n}(d_n) = \frac{\hat{C}_{gap,n}}{d_n}, \tag{2}
\]

where \( \rho_{mat,n}(c) \) denotes the conductivity of the \( n \)-th sensitive material when sensing target conditions being \( c \), and \( \hat{C}_{gap,n} \) denotes capacity of the gap with a unit width. Then, as shown in Fig. 1 (c), the total impedance of the meta-IoT sensor can be expressed as

\[
Z(f, c, d) = \left( \sum_{n=1}^{N_T} Z_n(f, c, d_n)^{-1} + \frac{N_T-1}{2\pi f C_{cp}} \right)^{-1}, \tag{3}
\]

where \( C_{cp} \) denotes the capacity due to the coupling between adjacent meta-IoT units, and \( d = (d_1, \ldots, d_{N_T}) \).

For the meta-IoT sensor, its reflection coefficient is a parameter that describes the fraction of the wireless signals reflected by an impedance discontinuity in the transmission medium [10]. In this paper, to facilitate the design of meta-IoT systems, we focus on the reflection coefficient which describe the ratio between the reflected and incident power. Based on [10], the reflection coefficient can be analytically modeled by

\[
\hat{\gamma}(f, c, d) = \frac{|Z(f, c, d) - Z_0|^2}{|Z(f, c, d) + Z_0|^2}, \tag{4}
\]

where \( Z_0 = 377 \, \Omega \) is the impedance of free space.

By substituting (1), (2), and (3) into (4), we can observe that the reflection coefficient of the meta-IoT sensor is dependent on \( d \). Therefore, the gap widths of the \( N_T \) meta-IoT units can be considered as the variables to design the meta-IoT sensor, which are thus referred to as the meta-IoT structure vector.

Using the analytical model derived above, i.e., \( \hat{\gamma}(f, c, d) \), we reveal the influence of \( d \) on the reflection coefficients. Nevertheless, to obtain a precise reflection coefficient function, numerical full-wave simulation and practical experiments are in need, which is of high computational time. Therefore, to reduce the time consumption required in optimizing \( d \) while ensuring the effectiveness of the results, we use \( \hat{\gamma}(f, c, d) \) and an additional interpolation function together to fit the precise reflection coefficient function over a sampled set of \( d \) denoted by \( D_X \). The resulting model-based fitting function is denoted by \( \hat{\gamma}(f, c, d) \) and used in the following optimization of \( d \).

III. SYSTEM MODEL

In this section, we first describe components of the meta-IoT sensing system, and then establish the transmission model.

A. System Description

The meta-IoT sensing system consists of a wireless transceiver and an array of meta-IoT sensors, as shown in Fig. 2. The meta-IoT sensor array is composed of \( N_x \times N_y \)
A small environmental signals and the power measurement area of the meta-IoT sensor array shown in Fig. 2.

The wireless transceiver consists of a processing unit and a pair of Tx and Rx antennas, which can be potentially carried by different devices, such as access points, base stations, or unmanned aerial vehicles [11]. The transceiver is capable by different devices, such as access points, base stations, or unmanned aerial vehicles [11]. The transceiver is capable of transmitting and receiving signals within frequency range \([f_{1b}, f_{ah}]\). The processing unit uses a sensing function denoted by \(g\) to map the power of received signals to the sensing target conditions.

**B. Transmission Model**

Denote the transmit power by \(P\), and with the help of [3], we can model the received signal power as

\[
P_{Tx, dB}(f, d; c) = 10 \log_{10}(\overline{P_{Tx, Rx}}(f)) \cdot (\eta_{env} \cdot P \cdot R_W + \eta_{ms} \cdot P \cdot \gamma(f, c, d)) + P_b + e(f),
\]

where \(\alpha\) is the path loss index, and \(D\) denotes the distance between the antenna and the meta-IoT sensor, i.e., the measurement distance.

1) **Pathloss:** Based on [12], the pathloss can be modeled by

\[
\overline{P_{Tx, Rx}}(f) = \left(\frac{\alpha}{4\pi f}\right)^2 \cdot \frac{1}{D^\alpha},
\]

where \(\alpha\) is the path loss index, and \(D\) denotes the distance between the antenna and the meta-IoT sensor, i.e., the measurement distance.

2) **Reflection:** The reflection part is composed of two terms. The first term, i.e., \(\eta_{ms} \cdot P \cdot \gamma(f, c, d)\) indicates the power reflected by the meta-IoT sensors. Here, \(\eta_{ms}\) and \(\eta_{env}\) can be calculated by

\[
\eta_{ms} = \frac{A}{S_0 \cdot (D/D_0)^2}, \quad \eta_{env} = 1 - \eta_{ms},
\]

where \(S_0\) denotes the coverage area of the antenna’s radiation on the plane at unit distance, and \(A = N_T^2 N_x N_y\) is the area of the meta-IoT sensor array shown in Fig. 2.

3) **Bias:** The bias at the wireless receiver accounts for the ambient environmental signals and the power measurement bias of the receiver. The bias \(P_b\) is modeled as a constant value that is much smaller than the transmitted power \(P\).

4) **Noise:** We model measurement noise \(e(f)\) of the wireless transceiver as a random variable following Gaussian distribution \(N(0, \sigma^2_N)\), where \(\sigma^2_N\) denotes the variance of the measurement noise.

**IV. Joint Meta-IoT Structure and Sensing Function Optimization Problem**

In this section, we formulate a joint meta-IoT structure and sensing function optimization problem for meta-IoT sensors to optimize the sensing performance of the meta-IoT sensing system, where the influence of both the sensing and transmission is considered jointly to minimize sensing errors.

To evaluate the sensing error, we adopt the root mean squared error (RMSE) as the loss function. Besides, the optimization variables are the meta-IoT structure, i.e., \(d\), and the parameters of the sensing function, which are coupled together in the formulated optimization problem. Specifically, the joint meta-IoT structure and sensing function optimization problem is formulated as

\[
(P1): \min_{w, d} L_{\text{RMSE}}(w, d) = \left( \sum_{j=1}^{N_c} \sum_{n=1}^{N_T} \| \tilde{c}_{j,m} - c_j \|_2^2 / N_C N_M N_T \right)^{1/2},
\]

\[
s.t. \quad (p_{j,m}, c_j) \in D, \quad \forall j \in [1, N_C], m \in [1, N_M],
\]

\[
(8)
\]

\[
\tilde{c}_{j,m} = g^w(p_{j,m}), \quad \forall j \in [1, N_C], m \in [1, N_M],
\]

\[
(9)
\]

\[
p_{j,m} = \left( p_{Rx, dB}^{\text{env}}(f_1), \ldots, p_{Rx, dB}^{\text{env}}(f_{N_F}) \right),
\]

\[
\forall j \in [1, N_C], m \in [1, N_M],
\]

\[
(10)
\]

\[
p_{Rx, dB}^{\text{env}}(f, d, c_j) = 10 \log_{10}(\overline{P_{Rx, Rx}}(f)) \cdot (\eta_{env} \cdot P \cdot R_W + \eta_{ms} \cdot P \cdot \gamma(f_1, c_j, d) + P_b) + e_{j,m}^{\text{env}},
\]

\[
\forall j \in [1, N_F], m \in [1, N_M], j \in [1, N_C],
\]

\[
(11)
\]

\[
d \in D_A,
\]

where \(N_F\) denotes the number of measurements.

In the objective function of (P1), \(N_C\) is the number of considered sensing condition vectors, \(N_M\) denotes the number of measurements given each sensing target condition vector, \(\tilde{c}_j\) indicates the \(j\)-th considered sensing target condition vector, and \(\tilde{c}_{j,m}\) is the estimated sensing target condition vector for the \(m\)-th measurement at \(c_j\). Constraint (8) indicates that the \(N_M N_C\) measurements given \(N_C\) sensing target condition vectors constitute the data set to minimize the RMSE of the system, where \(p_{j,m}\) denotes the \(m\)-th received power vector at \(c_j\). Constraint (9) is due to that the sensing target condition vector is estimated by using \(g^w\). Constraints (10) and (11) indicate the received power vector is determined by the wireless propagation channel, which is influenced by the sensing targets and the meta-IoT structure. Specifically, superscript \((m)\) denotes the result of the \(m\)-th measurement. Besides, in (12), \(D_A\) denotes the set of available meta-IoT structure vectors, which is a continuous set.

Nevertheless, due to the simultaneous sensing and transmission of the meta-IoT sensor, the meta-IoT structure, i.e.,
difference with the $j$-th sensing target condition vector at each sensing target condition, i.e.,
\[ N_j = \bigcup_{n=1}^{N_T} \{ j' | \arg\min_{j' \neq n} \sum_{n'} \| c_{j',n'} - c_{j,n} \| \}, \]  
(15)

where \( \mathcal{X} = \{ \arg\min_{\rho \in [1, N_c], \rho \neq n} | c_{\rho,n} - c_{j,n} | \} \),
where \( c_{j,n} \) indicates the \( n \)-th element of vector \( c \). It can be observe in (15) that \( |N_j| \leq 2N_T \). Therefore, the computational complexity of \( I_{EN} \) is \( O(N_c) \), which is much smaller than that of \( I_{ED} \). Besides, the error probability \( P_{err}(c_j \mid c_j) \) can be calculated with the help of Proposition 1.

**Proposition 1.** Assume that the maximum likelihood decision criterion is adopted to judge between the sensing target condition vectors. Then, for a given meta-IoT structure \( d \), \( P_{err}(c_j \mid c_j) \) can be calculated by
\[ P_{err}(c_j \mid c_j) = 0.5 \cdot (1 - \text{erf} \left( \frac{\sum_{n=1}^{N_T} (c_{j,n} - c_{j,n})^2}{2\sqrt{2}} \right)) \]  
(16)

where \( \text{erf}(\cdot) \) denotes the error function, and \( \tau_{j,i} = \tau_{j,i} \) is \[ \tau_{j,i} = 10 \log_{10} (P_L \cdot T_x \cdot T_x (f_i) - P_t \cdot \eta_{env} R_W + \eta_{ms} \cdot (f_i, c_j, d) + P_t). \]  
(17)

Moreover, \( P_{err}(c_j \mid c_j) \) decreases as transmit power \( P \) increases or as measurement distance \( D \) decreases.

**Proof:** See Appendix A.

Therefore, based on (P1) and (14), the meta-IoT structure optimization problem can be formulated as follows, where we minimize \( I_{EN} \) by optimizing \( d \).

\begin{align*}
(sP1): \min_d & \quad I_{EN} = \sum_{j,j' \in [1, N_c]} P_{err}(c_j \mid c_j), \\
\text{s.t.} & \quad (12), (15)-(17).
\end{align*}

Due to that the objective function in (sP1) contains a non-convex function, i.e., \( \text{erf}(\cdot) \), (sP1) is a non-convex optimization problem that is hard to solve. To solve (sP1) efficiently, we adopt the surrogate optimization algorithm [15], which can handle finitely bounded non-convex optimization problems and has a high probability of finding a global optimum.

2) Sensing Function Optimization Algorithm: In the sensing function optimization, we adopt the optimized meta-IoT structure, i.e., \( d^* \), and minimize the RMSE of the sensing by optimizing \( w \), i.e.,

\begin{align*}
(sP2): \min_w & \quad L_{RMSE}(w, d^*) = \left( \sum_{(p_{j,m}, c_j) \in D} \| c_{j,m} - c_j \| \right)^{1/2} \\
\text{s.t.} & \quad (3)-(10).
\end{align*}

To solve (sP2), we model that \( g^w \) as a fully connected neural network, which is an efficient model for general types of classification and regression functions. The fully connected neural network consists of an input layer, a hidden layer, and an output layer, which are connected successively. The input layer takes the \( N_F \)-dimensional real-valued received power vector, passes it to the hidden layer which contains \( N_W \) neural nodes, each of which calculates a biased weighted sum of its input

**V. ALGORITHM DESIGN**

In this section, we propose an efficient algorithm to solve the formulated problem (P1). In (P1), the main challenges lie in \( d \) affects both meta-IoT sensors’ sensitivity towards the sensing targets and the transmission, and optimization of \( d \) and \( w \) being coupled. To handle these challenges, we decompose (P1) into two sub-problems, i.e., **meta-IoT structure optimization**, and **sensing function optimization**, and solve them sequentially.

1) Meta-IoT Structure Optimization Algorithm: The meta-IoT structure optimization is based on the following intuition.

Consider \( g^w \) as a general classification function, which recognizes the sensing target conditions corresponding to a received power vector. Then, to optimize the potential performance of \( g^w \) requires to minimize the indiscernibility of the received power vectors for different sensing target condition vectors.

One widely adopted indiscernibility measurement is the Euclidean distance, which is used to evaluate the extent that two vectors can be discerned from each other [14]. For example, the average negative Euclidean distance can be used to measure the indiscernibility of the received power vectors in the meta-IoT system, which can be calculated by
\[ I_{ED} = -\frac{1}{N_c} \sum_{j,j' \in [1, N_c]} \frac{\| \hat{p}_j - \hat{p}_{j'} \|_2^2}{2}, \]  
(13)

where \( \hat{p}_j \) denotes the expectation of \( p_{j,m} \), i.e., neglecting the influence of measurement noise.

Nevertheless, using \( I_{ED} \) to measure the indiscernibility is inaccurate and inefficient for the considered meta-IoT sensing system. Intuitively, two sensing target condition vectors which are largely different from each other will result in significant differences between their corresponding received power vectors, which makes them highly distinguishable. Thus, the indiscernibility should be majorly due to the received power vectors of neighboring sensing target condition vectors which are similar to each other. Besides, calculating \( I_{ED} \) in (13) is of the computational complexity \( O(N_c^2) \), which is time-consuming when \( N_c \) is large. To handle the above issues, we adopt the error probability for judging nearest neighbors as the indiscernibility measurement for the received power vectors, which is
\[ I_{EN} = \sum_{j=1}^{N_c} \sum_{j' \notin N_j} P_{err}(c_j \mid c_j), \]  
(14)

where \( N_j \) denotes the index set of nearest neighbors of the \( j \)-th sensing target condition vector, and \( P_{err}(c_j \mid c_j) \) denotes the error probability to judge the \( N_T \) sensing target conditions to be \( c_{j'} \) when the actual conditions are \( c_j \). Specifically, nearest neighbor set \( N_j \) in (14) is composed of the sensing target condition vectors which have the smallest positive or negative
and processes the sum with a softmax function [14]. Then, the nodes in the hidden layer pass the results to the output layer, which consists of \( N_T \) neural nodes, which output the estimated sensing target conditions. In this case, the parameter vector of the sensing function, i.e., \( w \), stands for the connections of the weights and biases of the nodes.

Moreover, to obtain training data set \( \mathcal{D} \) in (8), we use the Monte Carlo method. In the simulation, we generate a set of random received power vectors satisfying the constraints in (82) which constitutes \( \mathcal{D} \), i.e.,

\[
\mathcal{D} = \{(p_{j,m}, c_j)|p_{j,m} = e + \tau^*(c_j), e = (e_1, \ldots, e_{N_E}), e_i \sim \mathcal{N}(0, \sigma^2_{e,i}), i \in [1, N_E], j \in [1, N_C], m \in [1, N_d]\},
\]

where \( \tau^*(c_j) \) is a \( N_E \)-dimensional vector with its \( i \)-th element being \( \tau_i^*(c_j) = 10\log_{10}(P_{\text{PL},\text{Tx},\text{Rx}}(f_i) \cdot (\eta_{\text{env}} \cdot P \cdot \eta_{\text{ms}} \cdot \gamma(f_i, c_j, d^*) + P_0)) \), and \( e \) is a \( N_E \)-dimensional vector of independently distributed Gaussian random variables.

Then, we optimize \( g^w \) by training it on \( \mathcal{D} \) using the supervised learning technique [14]. The training of \( w \) is performed by iteratively updating \( w \) along the negative gradient of the RMSE loss in (82), i.e.,

\[
w = w - \beta \nabla_w L_{\text{RMSE}}(w, d^*),
\]

where the gradient \( \nabla_w L_{\text{RMSE}}(w, d^*) \) is calculated by using the back-propagation algorithm [14], and \( \beta \in [0, 1] \) denotes the learning rate. Sum up the algorithm to solve sub-problems (8P1) and (8P2), and we can summarize the complete algorithm to solve (P1) as Algorithm 1.

**VI. Simulation Results**

In this section, we provide simulation results of the proposed algorithm, which validates the effectiveness of the algorithm and the meta-IoT system. Besides, we give insight into how the transmit power and the measurement distance influence the sensing accuracy.

In the simulation, each meta-IoT sensor consists of two meta-IoT units. The first meta-IoT unit has temperature-sensitive material within its gap and is aimed for sensing temperature, which we refer to as the \( T \)-unit. Similarly, the second meta-IoT unit contains humidity-sensitive material for sensing humidity and is referred to as \( H \)-unit. More specifically, the meta-IoT units are made of copper rings and FR-4 supportive substrate, and the detailed setting parameters are shown in Table I. The adopted temperature-sensitive material in \( T \)-unit is the powder used in the NTC thermistor SDNT2012X102-3450-TF [16]. Besides, the adopted humidity-sensitive material in \( H \)-unit is the polymer used in the hygro sensor TELAiRE HS30P [17]. Moreover, the selected sensing target condition set is \( C = \{(c_1, c_2) | c_1 \in [5, 45], c_2 \in [20, 60], c_1, c_2 \equiv 0 \mod 5 \} \), and thus \( N_C = 81 \). By solving (P1) given the above simulation settings, we obtain the optimal meta-IoT structure \( d^* = (2.05, 1.22) \) mm.

Figs. 3 and 4 show the resulting RMSE obtained by solving (8P2) under different cases of meta-IoT structure. In both Figs. 3 and 4 the first case indicates the resulting RMSE of the meta-IoT system with the optimal meta-IoT structure found within \( \mathcal{D}_A = \{ d \in \mathbb{R}^2|d_T, d_H \in [1, 5] \text{ mm}, d_T \neq d_H \} \). The second case indicates the resulting RMSE of the meta-IoT system given the optimal integer meta-IoT structure found within \( \mathcal{D}_A = \{ d \in \mathbb{Z}^2|d_T, d_H \in [1, 5] \text{ mm}, d_T \neq d_H \} \), which is denoted by \( d^*_G \). The third case indicates the average resulting RMSE of the meta-IoT system given meta-IoT structures in \( \mathcal{D}_A \). It can be observed that the optimal meta-IoT structure obtained by using Algorithm 1 outperforms the other meta-IoT structures in terms of the resulting RMSE.

Besides, it can be observed that the resulting RMSE values of different meta-IoT structures decrease as the transmit power increases, and increase as the measurement distance increases, which are in accordance with the analysis in Proposition I. Moreover, the optimal meta-IoT structure leads to the lowest RMSE under different transmit power and distance.
Using the maximum probability criterion, the probability to decide on \( c_j \) from \( p_j \) can be calculated by
\[
\Pr(p_j|c_j) = \frac{\prod_{i=1}^{N_f} e^{-\frac{(c_i - \tau_{j,i})^2}{2\sigma_M^2}}}{\sqrt{2\pi\sigma_M^2}}.
\]
By taking partial derivative, it can be proven that \( \frac{\partial \sigma_{j,i}^2}{\partial P} > 0 \), indicating that the error probability decreases as the transmit power increases. Similarly, by taking the partial derivative with respect to \( D \), it can be proven that \( \frac{\partial \sigma_{j,i}^2}{\partial D} < 0 \), indicating that the error probability decreases as the measurement distance decreases.

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