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Machine Learning Approach for Wirelessly Powered RFID-based Backscattering Sensor System

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Abstract—**A RFID-based backscattering sensor system is low-cost and scalable wireless sensing technology. It takes advantage of RF energy harvesting technique, wireless power transfer and backscattering principle. It also has uncountable number of applications due to its versatility. In this paper, operation principle, architecture and machine learning technique for wirelessly powered RFID-based backscattering sensor system is presented. For the sensor tag-reading and power-delivering algorithm, machine learning techniques, such as support vector machine (SVM), artificial neural networks (ANN), and naive Bayes algorithm, are introduced with experimental verifications. The supervised SVM algorithm significantly improved reading accuracy of chipless RFID sensor tags due to superior signal classification performance of the SVM method. The ANN-based adaptive dynamic matching network for magnetic resonant wireless power transfer system improved wireless power transfer distance efficiently. Position estimation method based on the naive Bayes algorithm that is essential for smart wireless power transfer platform for wirelessly powered drones is also discussed in this paper.**

Index Terms—**Backscattered radio, far-field energy harvesting, machine learning, printed sensor, RFID-based sensor, RFID tag, supported vector machine (SVM), artificial neural networks (ANN), naive Bayes, wireless power transfer.**

I. Introduction

A novel low-power, low-cost wireless sensor system for large scale Internet of Things (IoT) is an essential technology for the hyper-connected society [1]. Recent advances in 5G communications have expedited this evolution [2,3]. Smart wireless sensor networks or massive IoT embedded systems, such as smart factories/hospitals or self-driving cars, transmit and process huge amount of collected data in few milliseconds thanks to the ultra-fast communication speed (up to 20 Gbps) and ultra-reliable low latency (URLL) of the 5G communication networks. In this point of view, the energy harvesting or wireless power transfer technology enabled RFID-based backscattering sensor system has many advantages for the self-sustainable extremely low-power wireless sensor applications. It has relatively simple system architecture, low-cost, long life time, broad sensing capability, and inherited passive ('zero' power) operation [4,5]. It is also relatively convenient to integrate the RFID-based wireless sensor systems into other pre-built wireless sensor/communication networks. Remarkable advances of artificial intelligence (AI), especially for the machine learning techniques, has brought groundbreaking innovations in RFID-based self-sustainable sensor systems [6].

There are numerous reported research efforts on AI (machine learning) and their various applications [7-9]. The machine learning technology has improved many challenging problems dramatically, such as pattern recognition and cyber security. The machine learning technique is also able to bring unprecedented benefits and features to RFID-based 'zero' power wireless backscattering sensor system. There are three types of machine learning approach: supervised, unsupervised and reinforced. The unsupervised learning extracts inherent data structures from unlabeled data sets without feedback. It is able to find hidden structures or features of a given data set. The reinforced learning, unlike the supervised and unsupervised learning, recognizes the current state and takes action to maximize rewards in a series of actions or all decision-making processes. The supervised learning trains a machine using direct feedback from given labeled data sets and outputs. Outcome prediction or data classification are suitable applications for the supervised learning. The supervised learning is able to play a pivotal role in analyzing backscattered digital/analog signals or wireless power transfer system because most of signal processing in wirelessly powered RFID-based sensor systems is a classifying or a decision-making process.

This paper presents recent progress of ultra-low power wirelessly powered RFID-based backscattering sensor system assisted by supervised machine learning algorithms: supported vector machine, artificial neural network, and naive Bayes. Topology (single-tag or multi-tags) and operation principle of RFID-based sensor tag are covered. Machine learning assisted smart wireless power transfer algorithms are also included in this paper because efficient wireless power transfer algorithm is important for the self-sustainable operation of wireless sensor

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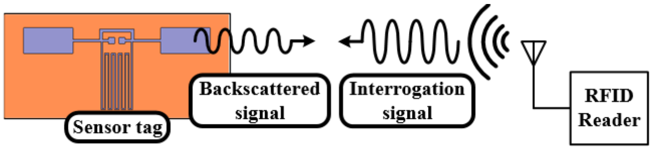

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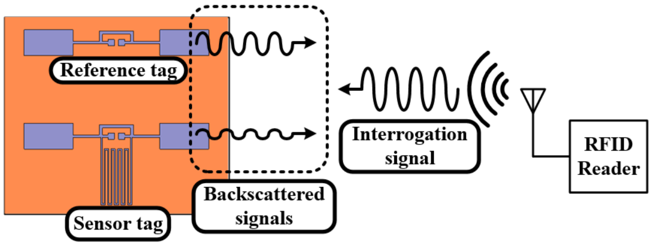

(b)

Fig. 1. Types of RFID-based sensor: (a) single-tag and (b) multi-tag systems.

networks. Dynamic matching network based on artificial neural network (ANN) and naive Bayes algorithm for adaptive wireless power transfer system experimentally demonstrated feasibility of machine learning techniques for self-sustainable wireless communication and sensor platform. The supervised SVM algorithm significantly improved reading accuracy of chipless RFID sensor tags due to superior signal classification performance of the SVM method. The ANN-based adaptive dynamic matching network for magnetic resonant wireless power transfer system improved wireless power transfer distance efficiently. Position estimation method based on the naive Bayes algorithm that is essential for smart wireless power transfer platform for wirelessly powered drones is also discussed in this paper.

Rest of paper is organized as follows. In Section II, the operation principle of the self-sustainable RFID-based sensor system is presented. In Section III, the supervised machine learning algorithms for the self-sustainable sensor platform, such as wireless power transfer technology enabled RFID-based sensor, is discussed to develop an AI-assisted self-sustainable wireless sensor system.

II. RFID-BASED BACKSCATTERING SENSOR SYSTEM

Many RFID-based backscattering sensor tags are passive tags because of their relatively straightforward operation principle [10]. There are two types of RFID-based sensing topologies: single-tag or multi-tag sensing. The single-tag RFID sensor detects events using only one sensor tag, while the multi-tag RFID sensor employs two or more tags to make a decision (event detection). A single-tag sensor system is relatively simple, small, and low-cost system but a reader requires more functionalities, such as calibration and data analysis algorithm, than the multi-tag sensor systems. The single-tag sensor system collects remote sensing data from each sensor tag but the multi-tag sensor system has reference data for comparison as shown in Fig. 1.

The RFID-base sensor system consists of a reader and sensor tags. The sensor tag is a RFID tag integrated with a sensing component. The sensor tag harvests radiated electromagnetic power from the reader, and re-radiates (or backscatters) modulated signal to the reader. There are many types of sensing components, such as inductive or capacitive sensors, that modulate the incident wireless signals [11-14]. Some reported research efforts on RFID IC chips already have sensing capabilities [12]. Chipless RFID tags which do not have RFID ICs reflect (backscattering) incident interrogation signals, and the backscattered electromagnetic waves are modulated by resonators or sensing components [15,16].

Role of a reader (or an interrogator) is critical since the antenna of the RFID-based sensor tags interact with their surrounding environment resulting in unwanted frequency, phase, or magnitude (Radar Cross-section, RCS) shifts. The reader should process the collected sensor data correctly to prevent false alarms or malfunctions. Software defined radios (SDRs) are widely used in reader implementations of RFID-based sensor systems due to their flexible RF front-end (RFFE) re-configurability [17-20]. The SDR platform consists of reconfigurable, intelligent and software programmable hardware elements. Moreover, there are numerus available open application programming interfaces (APIs), such as Python, C/C++, and GNU radio, for flexible SDR platform management. Python for SDR has attracted interests of many researchers because the machine learning algorithms are built in its library. Therefore, both TRx RF front-end system of SDR and down-converted baseband signals for machine learning can be processed on the Python platform.

Requirements of reader antennas for RFID-based sensors and conventional RFID systems are very similar, but there are some distinctive differences. Conventional RFID reader system uses a circularly polarized (CP) high gain antenna for fixed type readers since the orientation of the RFID tags is usually unknown. CP waves radiated from the reader antenna deliver RF power to linearly polarized tags with 3 dB power loss, but alleviate tag orientation issues. Broadside or end-fire radiation pattern is preferred for the RFID reader antenna to focus the EM energy on the tags. However, RFID-based sensor systems sometimes utilize polarization diversity of vertical (*V*-pol) and horizontal (*H*-pol) polarizations. For example, *H*-pol waves carry a Tx signal from a reader, and a modulated backscattered waves are *V*-polarized (Rx). The radiation pattern of the reader antenna depends on the applications. Bistatic multi-node sensor systems require both of omni-directional and end-fire antennas, while monostatic sensor systems require dual polarized end-fire antenna or of two linearly polarized high gain antennas [21].

Fig. 2 shows a simplified equivalent circuit model and operation principle of the RFID-based backscattering sensor system. A dipole type RFID tag antenna is modeled as a series RLC tank (R_a, L_a, and C_a), and the resonator type sensor component is also shown in Fig. 2(a). The sensing component is the load on the RFID tag that modulates the backscattered signal when the main sensing component value changes (R_s, L_s, and C_s). Capacitive or inductive sensor changes their capacitance or inductance value when the sensor detects an event. Resistance variation of a sensing component is also able to modulate backscattered or re-radiated signals from the sensor

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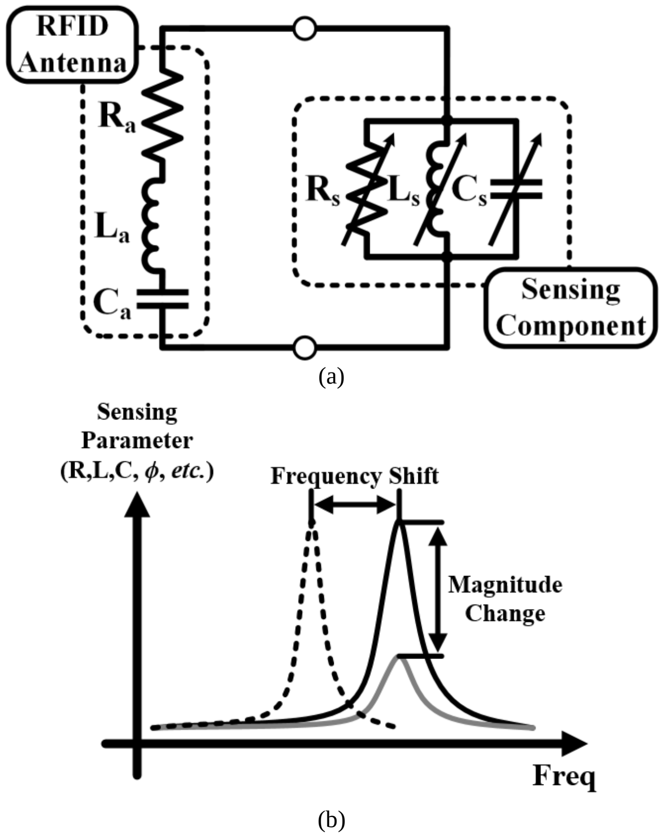

Fig. 2. Operation principle of the RFID-based sensor tag: (a) equivalent circuit model of the sensor tag and (b) frequency response of a sensor tag.

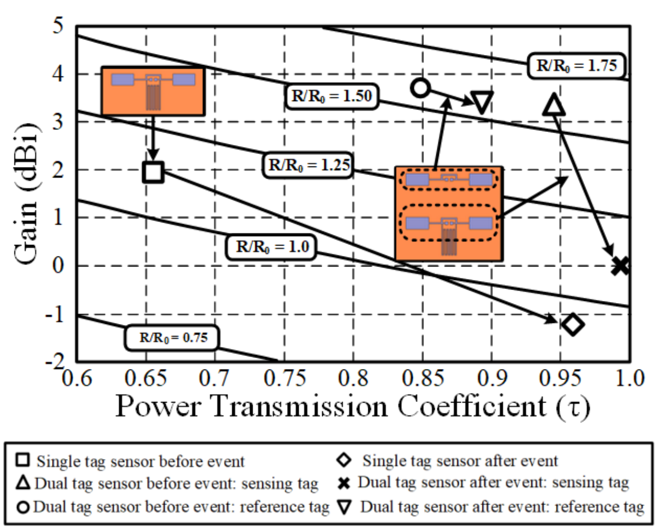

Fig. 3. Read-range analysis of RFID-based sensor tags.

tag. Any circuital changes of the sensing component affect the frequency response of the RFID tag (Fig. 2(a)). The reader analyzes the backscattered signals to detect resonant frequency shift, magnitude variation, or phase shift as shown in Fig. 2(b) [22-24].

Performance evaluation of sensor tags is also important for developing an optimized RFID-based sensor system. Calculated read-range analysis of the RFID-based sensor tags

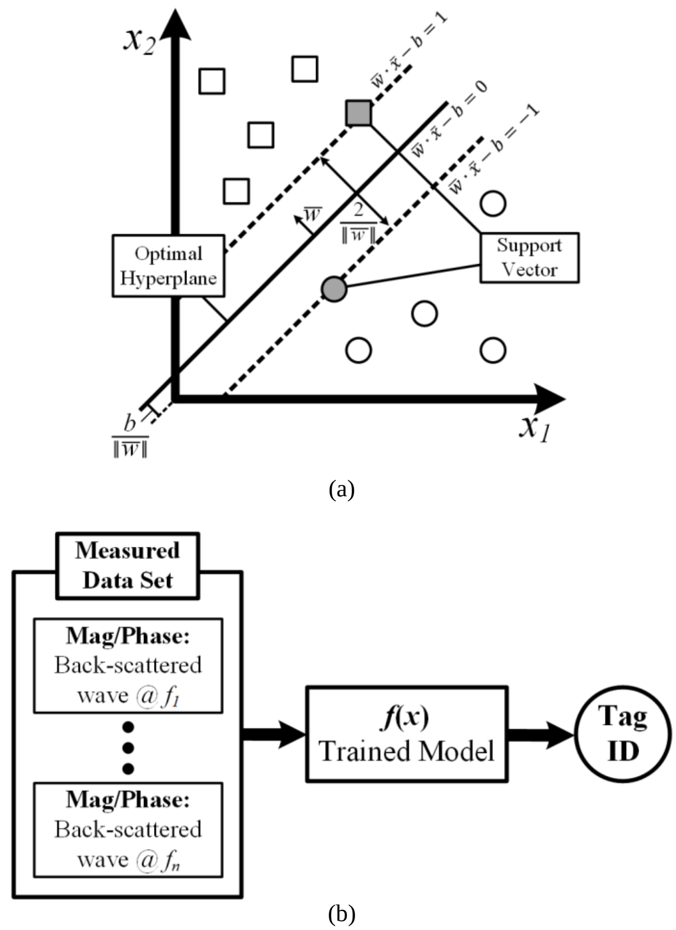

Fig. 4. (a) SVM classification and (b) its application to chipless RFID reader.

shown in Fig. 3 is a simple and convenient way to compare the performance of the RFID-based sensor tags [10]. Fig. 3 consists of two axes: power transmission coefficient (τ) and tag antenna gain. The power transmission coefficient indicates matching between the RFID chip and the tag antenna. For example, a value of 1.0 means perfect complex conjugate matching between the antenna and the RFID IC. R_0 is the estimated read-range of a perfectly matched RFID tag with 0 dBi linearly polarized antenna gain at the operation frequency. R is the read-range of the sensor tag. It is calculated according to the Friis equation, and the minimum power required to activate the passive RFID chip. An example of the normalized read-ranges of the reported sensor tag and other reported research efforts are shown in Fig. 3. The direction of the arrows indicates before and after the event occurrence.

III. Machine Learning Approaches

A. *Support Vector Machine (SVM) Method*

In this study, the supervised machine learning method is chosen to implement the RFID-based sensor tag-reading algorithm because of the limited data set that can be collected from the sensor tags. As a proof of concept, a simple chipless RFID tag is designed and a tag ID reading algorithm is built based on the SVM machine learning method [25]. Fig. 4(a)

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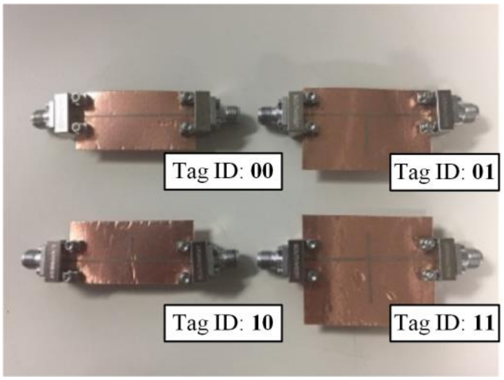

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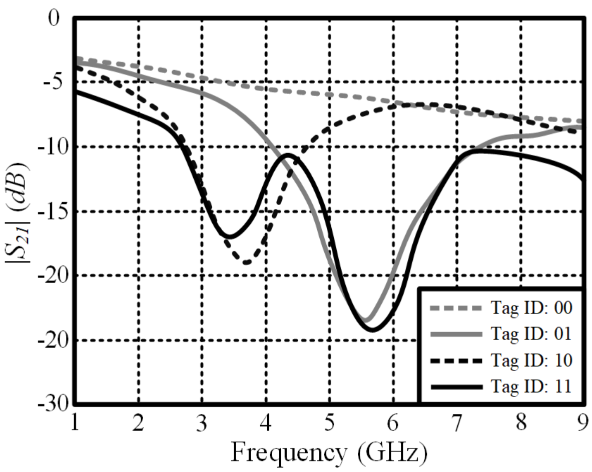

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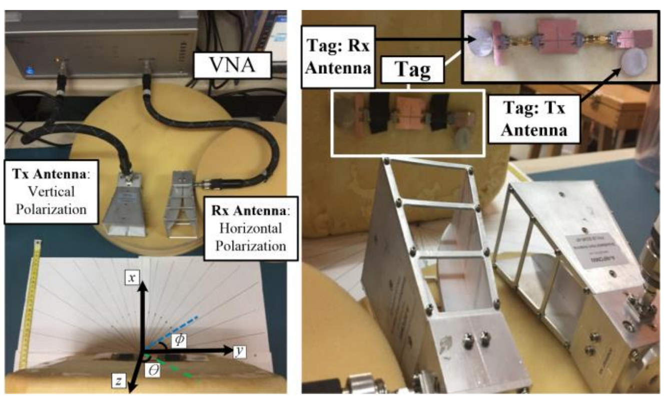

(c)

Fig. 5. (a) Printed chipless RFID tags, (b) wired measurement of tag ID for SVM machine learning data set collection and (c) measurement setup for tag reading.

shows a basic principle of the linear SVM [26]. The SVM algorithm constructs a set of $(N-1)$ dimensional hyperplanes in N-dimensional space to classify data points. A training data set of n points is written as $(\bar{x}_1, y_1), \cdots, (\bar{x}_n, y_n)$ where y_n ($y_n \in \{-1,1\}$) indicates the class of $\bar{x}_n$. The optimal hyperplane can be expressed with a normal vector ($\bar{w}$) as '$\bar{w} \cdot \bar{x} - b = 0$' where b determines the offset of the hyperplane. The optimal hyperplane is located in the middle of support vectors, which have the class value (y_n value) of -1 or 1 as

Table I. Accuracy Comparison: Train Models

Training Parameters	Decision Trees	Boosted Trees	*k-NN	**SVM**
†Mag.	59.6	73.7	67.0	89.6
Phase	56.0	64.4	52.5	74.0
Mag. & Phase	60.7	76.7	55.7	86.2
Real	58.1	68.7	56.1	**94.4**
‡Imag.	61.9	75.8	60.7	93.2
Real & Imag.	56.4	72.2	56.7	94.6
Mag. & Real	55.2	76.8	62.6	92.5
Mag. & Imag.	59.0	64.6	60.9	92.3
Mag. & Real & Imag.	57.4	74.5	59.9	90.0

*k-NN: k-Nearest Neighbors algorithm
†Mag.: Magnitude, ‡Imag.: Imaginary

shown in Fig. 4(a). In this point of view, the SVM machine learning algorithm is able to classify data, such as bit information ('0' or '1'), easily based on a given data set. For RFID-based sensor applications, a bit data set should be collected, and the reader is trained according to the SVM algorithm as shown in Fig. 4(b). The magnitude and phase information of each backscattered wave at certain frequency (f_n) is considered as a data set ($\bar{x}_n$) for SVM training . The full data set for machine training can be obtained by frequency sweeping. The RFID reader is able to make a decision (detect tag ID or sensor data) once a trained model is built.

As a design example, this paper presents a printed chipless RFID tag using stub resonators [25]. A two-bit tag ID was implemented using open stub resonators as shown in Fig. 5(a). The first and second bits were located at 3.45 GHz and 5.7 GHz, respectively. 'High' (bit '1') or 'Low (bit '0') was defined as the presence of resonance as shown in Fig. 5(b). In this work, 18 MHz step was set to frequency step because it is fine enough to detect resonance of the proposed chipless RFID tag. The frequency spacing between bits is 2 GHz, and design goal is to detect resonances at 3.45 GHz and 5.7 GHz. The Tx and Rx antennas were placed orthogonally, and connected to a vector network analyzer (VNA). 816 sets of measurement data were collected in total. $|S_{21}|$ was measured over 9 GHz (collected data bandwidth: 1 ~ 10 GHz) frequency span with 501 points per each measurement (18 MHz step) as an input data set for the SVM machine learning process. The designed chipless two-bit RFID tag was read over-the-air (OTA) as shown in Fig. 5(c), and received data sets were classified (read) by a trained SVM model. Transmitted (Tx) signals from the reader were vertically polarized while the received (Rx) signals were horizontally polarized. Random 163 datasets out of total 816 datasets were chosen as a training data set. The training process was stopped when the accuracy value shown in Table I was saturated. The accuracy of the proposed SVM machine was better than other training models, such as decision trees, boosted trees, and k-Nearest Neighbors (k-NN), as shown in Table I. The magnitude of the backscattered waves showed the most accurate training parameter among the many measurable EM wave parameters.

In the case of training, Fig. 5(c) shows a calibrated bi-static

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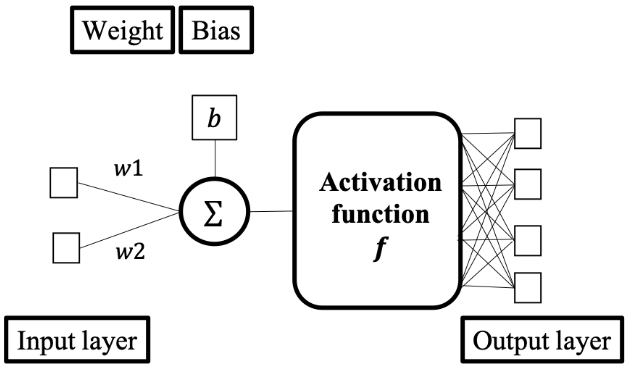


Fig. 6. Simplified building block of artificial neural networks (ANN).

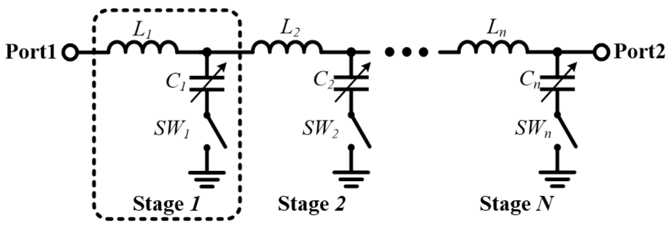


Fig. 7. Simplified N-stage active matching circuit topology for the proposed smart adaptive matching network.

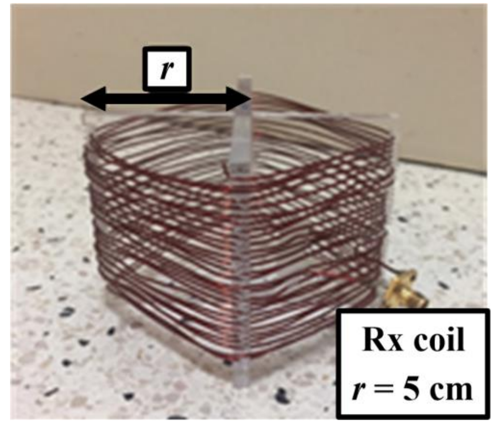
wireless measurement setup without a-priori knowledge (tag arrangement and clutter-generating elements). The tags used in the actual implementation were completely printed without any connectors. Exploring performance for high-density bit implementation is the subject of future research efforts.

B. Artificial Neural Networks (ANN)

The ANN is a set of algorithms that works to recognize basic relationships in a series of data inspired by neurons in the human brain. The ANN algorithm trains neurons associated with each weight factor that decides triggering speed based on the activation function. Bias, b, in Fig. 6 is an additional parameter in the neural networks, which delays triggering of the activation function and adjust the output based on the weighted sum of the inputs to the neurons.

In this study, a novel real-time range-adaptive dynamic impedance matching circuit network design for smart wireless power transfer (WPT) applications utilizing an ANN-based machine learning strategy is discussed [27]. As a proof of concept, a single Rx and three stacked Tx coils with a tunable matching circuit were designed. A proposed dynamic matching circuit consists of N consecutive L-type matching networks as shown in Fig. 7. A unit-matching network consists of a series inductor, a shunt varactor, and a PIN diode switch. Three unit networks are chosen based on ANN algorithm to achieve optimized power transfer efficiency at a given distance. Each series inductor has fixed inductance value, and its value was selected based on the capacitance range of the varactor at operation frequency range. This static topology is able to achieve acceptable power transfer efficiency values over a wide range of Tx-Rx distances.

For the experiment setup, two aligned helical coils resonating at 13.56 MHz are fabricated [28]. The Rx coil and selective concentric three Tx coils are proposed to maximize the coil-to-



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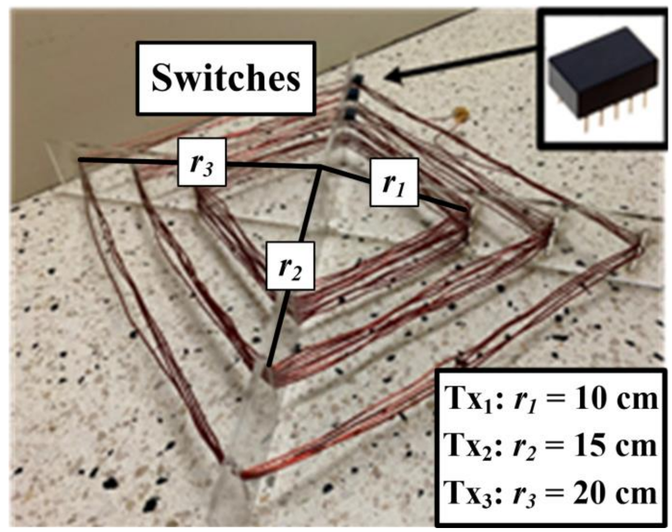


(b)

Fig. 8. (a) Fabricated Rx coil and (b) stacked concentric three Tx coils.

coil power transfer efficiency with the optimal radius of Tx coil as shown in Fig. 8. To confirm the effectiveness of using the selective Tx coils, the reflection coefficients ($|S_{11}|$) of coil-to-coil (Rx-Tx_1, Rx-Tx_2, and Rx-Tx_3) were firstly simulated as shown in Fig. 9, and the extracted S-parameter matrices serve a standard dataset for the neural network training. For the ANN training, the real and the imaginary parts of the impedance of the equivalent load ($\boldsymbol{Z}_{eq} = [R_{eq}, X_{eq}]^{\mathrm{T}}$) were used for an input parameter set (x) to approximate function $f(x)$ through the feedforward neural network. An output parameter set consists of capacitor values for the 3-stage adaptive matching network with the selection of optimal Tx coil ($[C_1, C_2, C_3, \mathrm{Tx}_n]^{\mathrm{T}}$). 220 data sets were generated from the distribution of $|S_{11}|$ values using the matching network to match impedances within the range of 0 to 20 Ω for R_{eq} and -50 to 50 for X_{eq}.

The training process using the feedforward neural network was implemented to predict the capacitance values and activate proper Tx coil. The measurement configuration consists of a directional coupler, the RF detector, and a microcontroller module with an analog-to-digital (ADC) converter to test the performance of the proposed system. The S-parameters of the matched state were measured at different coil separation distances, and the measured $|S_{21}|$ values were used to calculate

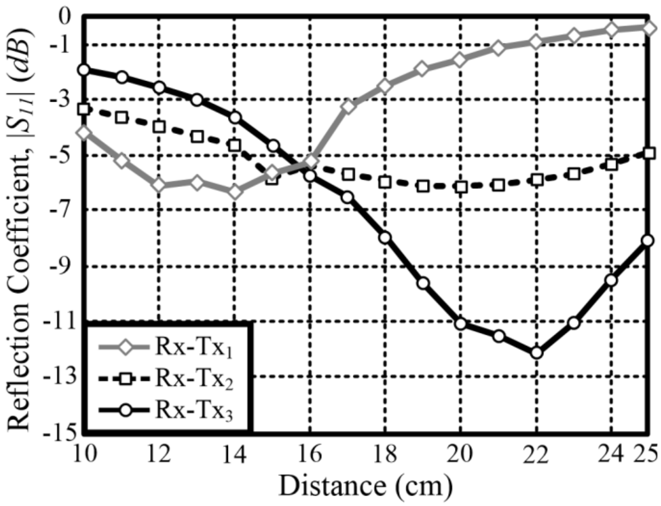


Fig. 9. Calculated $|S_{11}|$ according to distance between Tx and Rx coils.

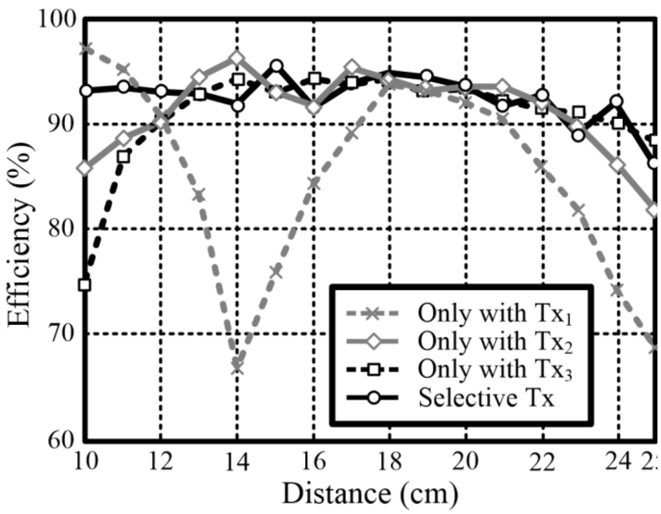


Fig. 10. Power transfer efficiency with and without the selective Tx.

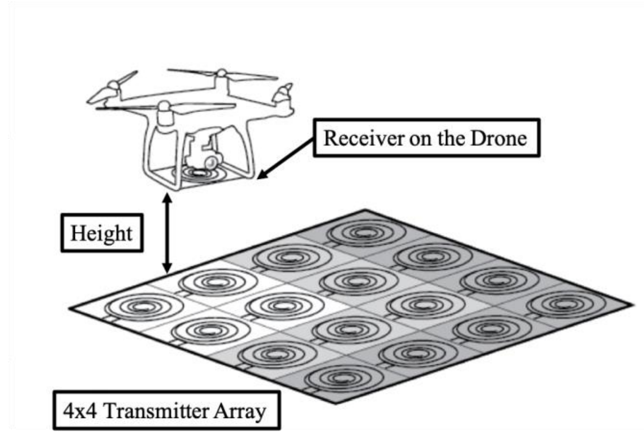
Table II. Wireless Power Transfer Efficiency

		k-means clustering method				ANN
Stages		1	2	3	4	3
Efficiency (%)	*k*-4	78.3	79.6	81.6	82.0	92 (Average)
	k-8	78.0	79.5	81.7	82.5	
	k-16	77.6	79.5	81.6	82.3	

the power transfer efficiency. The measured efficiency of the proposed system is shown in Fig. 10. The proposed approach achieved a power transfer efficiency of around 90% over the distance range within 10 ~ 25 cm. Table II shows the power transfer efficiency values utilizing unsupervised learning (*k*-means clustering) and proposed ANN methods. It is clear that the proposed ANN algorithm improved power transfer efficiency significantly.

C. Naive Bayes Algorithm

The importance of wireless energy transfer for moving objects, such as automotive vehicles and unmanned aerial vehicles (UAVs), is growing rapidly [29]. Three main keywords for wireless energy transmission to moving objects in this work are low power wide area networks, UAV, and wireless power transfer. Fig. 11 shows a novel wireless power transfer platform utilizing a machine learning strategy and a measurement setup, respectively. A Styrofoam with 9-position grid is placed on top of the Tx coil array to characterize the movement of the Rx coil mounted on the drone [30]. The proposed system consists of Tx coil array on the ground and a Rx coil mounted on a drone. An off-the-shelf planar coil is used for both Tx and Rx charging coils as shown in Fig. 12. The coils resonate at 13.56 MHz with a series connected capacitor.



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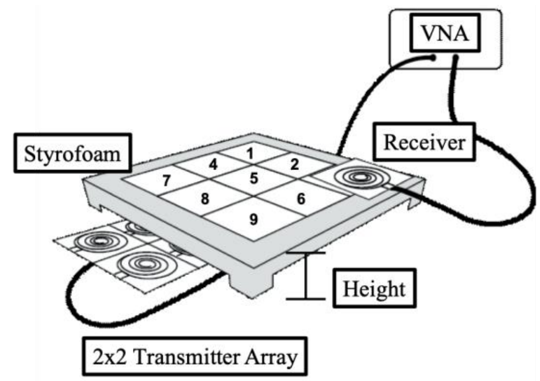
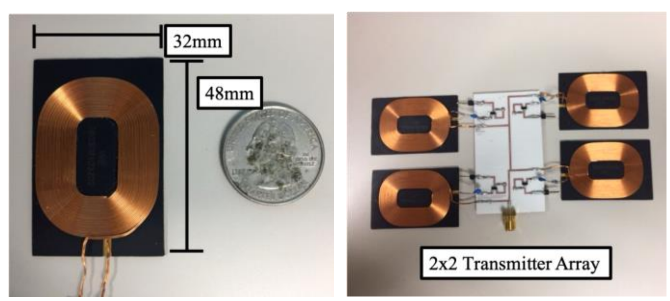


(b)

Fig. 11. (a) Schematic of the proposed WPT system with a drone and (b) its position measurement setup.



(a) (b)

Fig. 12. (a) A unit Tx charging coil and (b) a fabricated 2×2 Tx coil array prototype.

For this experiment, the naive Bayes algorithm is chosen due to its characteristics. The naive Bayes algorithm is relatively

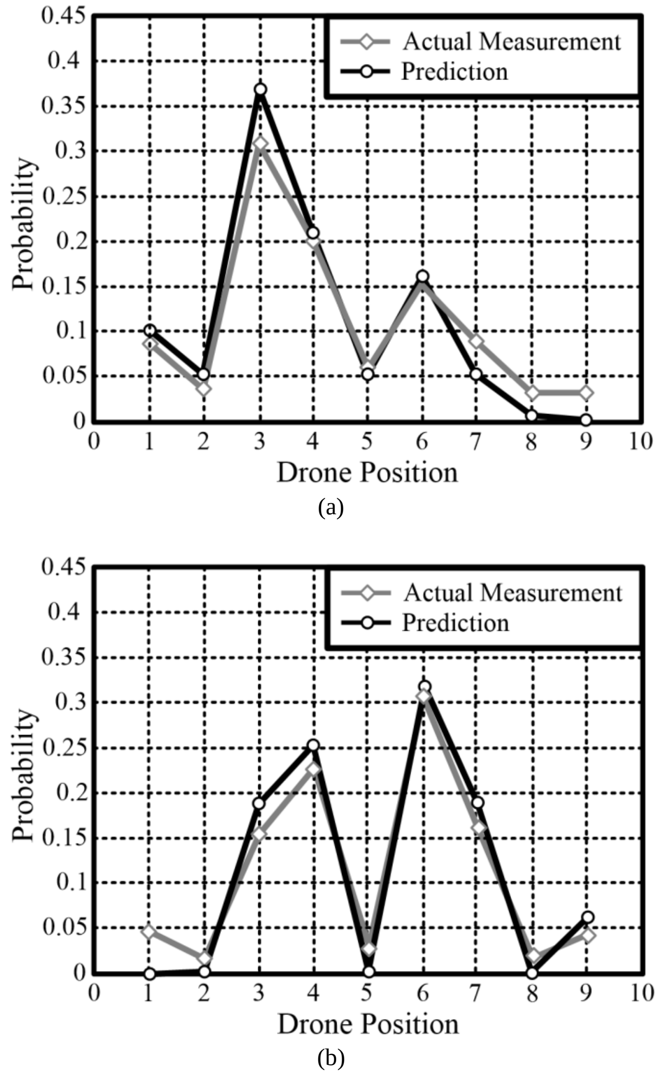


Fig. 13. Drone position prediction at (a) 1-inch height and (b) 1.25-inch height.

simple to implement and flexible enough to cover different types of measurement data. The naive Bayes algorithm calculate the various probabilities based on the 144 cases measured at different distances and the positions. The Bayes theorem provides a way of calculating the posterior probability, $P(C_k|x)$, from the prior probability of a class, $P(C_k)$, the likelihood which is the probability of predictor given class, $P(x|C_k)$, and the prior probability of predictor $P(x)$ as written in (1) and (2).

$$P(C_k|x) = \frac{P(C_k)P(x|C_k)}{P(x)} \quad (1)$$

$$P(x|C_k) = \prod_{i=1}^{n} P(x_i\,|C_k) \quad (2)$$

$P(x|C_k)$ is the conditional probability of seeing the evidence, x, if the hypothesis C_k is true. The method computes the posterior probability of that sample belonging to each class, then classifies the test data according to the largest posterior probability by the following equation (3).

$$y = \underset{k\in\{1,2,\ldots,k\}}{\operatorname{argmax}} P(C_k) \prod_{i=1}^{n} P(x_i\,|C_k) \quad (3)$$

Switching status of four Tx coils, height of a drone, measured power transfer efficiency are input parameters while the output parameter is a position number. Fig. 13 shows the prediction results compared to original measured data at two operation distances using the naive Bayes classification method. It is clear that the naive Bayes algorithm provides great performance for predicting the position of an Rx coil. This preliminary result paves a new way to a rich and wide area of research for the implementation of machine learning methods for the enhancement of wireless technology, such as RFID and WPT on UAV applications.

IV. Conclusion

This paper discussed various application scenarios of ultra-low power RFID-based backscattering sensor tags and machine-learning algorithms for self-sustainable wireless sensor platforms. Operation principle of the sensor tags and machine learning-based chipless RFID tag ID classification technique of the reader were presented in detail. SVM, ANN, and naive Bayes machine learning algorithms were implemented for RFID tag ID classification technique and wireless power transfer applications to improve the reading accuracy and communication range of the backscattering wireless sensor systems. The presented sensor system is a highly scalable technology, which can be extended to various research and industries. For example, “smart” business, such as smart farm, agriculture, bio-medical, and manufacturing facility applications, are future applications of the proposed zero-power self-sustainable machine learning assisted wireless sensor systems.

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