Prediction of RFID Systems Coverage Applied to Smart Cards Scenario

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Abstract — **RFID systems usually need to be applied where the installation cost can be very high, and thus, running a simulation in such environments would bring many benefits such as saving time and money. In this case, the simulation could be considered as a prediction method that verifies whether the configuration for the desired scenario works correctly and meets the system's requirements. This work presents a research about statistical prediction models for RFID systems' coverage in a specific scenario. In order to predict the RFID system coverage, the tag read count was measured in an indoor environment. In the chosen scenario, RFID technology is applied to smart cards. This research presents a model using Multiple Linear Regression and another approach using Artificial Neural Networks on the prediction of the read count. Results showed improvements on the prediction of area coverage, bringing advantages to RFID projects, such as less time and resources required to RFID systems deployment.**

Keywords *– RFID Prediction Model, RFID Environment Simulation, Artificial Neural Networks*

I. INTRODUCTION

One of the main tasks in the deployment of radio frequency identification (RFID) solutions is to design and install a test environment where the technology will be used. With this test environment, business managers and IT managers will realize that, indeed, an RFID solution can answer the business needs. Also, it's possible to study the impact of RFID technology in the business process. However, the cost of investment combined with the deployment of a test environment can be high for a medium-sized company, because of the equipment prices and the need for specialized workforce to develop an experimental case. Furthermore, the current system verification methods consist of conducting field experiments based on trial and error, which consumes too much time and money.

In order to decrease the costs associated with the deployment of a test environment, an alternative is to run environment simulations where the tests would be made. RFID system functioning prediction is not a trivial task, because the simulation challenge involves many communication layers.

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Furthermore, RFID system devices have a high sensitivity towards environmental interferences, such as communication signal reflection from other objects. As such, finding the components' position and configuration can be very difficult. A tool that can simulate the functioning of an RFID system can bring many benefits, such as the specification and the ease of change of scenario, less verification time and savings.

This paper has as main objective the development of a statistic prediction model to the RFID systems functioning in a specific scenario. In statistical models all environmental influences are implicitly taken into account regardless of whether or not they can be separately recognized [1]. To obtain the database needed by the model, field experiments were made. The specific scenario addressed in this paper contemplates RFID systems applied to personal identification cards. The goal of this kind of system is to register and identify people accessing certain places. In this kind of scenario, an RFID tag is attached to a badge, requiring no human intervention in the identification process. This solution is known as "smart cards".

In order to verify the functioning of an RFID system, it is proposed a novel approach where the model should result the RFID tag reading intensity, according to the values provided in the model variables and taking into consideration most of the influences present in the environment.

The paper seeks a novel approach towards RFID systems functioning prediction, with the tag read count being used to verify the RFID system coverage in the environment. It is also unknown any other research that takes into consideration the material of the internal walls of the environment as a simulation variable. Apart from that, this paper also considers scenarios where people are carrying badges, including in movement, a subject not well known in RFID researches.

The remainder of this paper is organized as follows. In section II we present related work. Section III presents the test environment and collected data analysis. Section IV presents the proposed models and results. And section V presents the conclusions and future work.

II. RELATED WORK

In relation to RFID prediction models, publications can be found about logical and physical layers simulation of the technology, and also papers that describe the working of both layers, such as anti-collision protocols and RF signal propagation researches. It is not known in literature, a research concerning about RFID systems coverage based on smart cards scenario.

Approaching the physical layer of the technology, [2] presents a detailed study about RFID signal propagation, considering many technical and physical devices characteristics, however no use environment models are presented.

In [3], it is presented a study focused in RF propagation of RFID devices with the human body located close to a tag. The test is specific for Alien Squiggle tags [4]. In the research the environment is not considered, and the power and frequency factors of RFID systems are analyzed.

In [5], Floerkemeier and Sarma presented RFIDSim (RFID simulation engine). RFIDSim is a tool that simulates in a discrete event machine the anti-collision algorithms operation and the physical operation aspects of an RFID system. The simulation of the physical layer is based on the RF pathloss propagation and Rician-fading models. [5] presents a simulation tool that takes in consideration some of the many aspects that influence in the RFID systems communication. The tool configuration is based on the power n used in the signal loss equation. The availability of new propagation models, with more environment configuration flexibility, such as the presented in this paper, can be an important evolution for the referred tool.

In [1], it is presented a prediction model for the RF signal intensity field in indoor environments. Although the model is not focused specifically on RFID technology, it addresses the basic principles of RF signal propagation. The model is based on the feedforward Artificial Neural Networks (ANN) with retro-propagation. In this paper, the prediction variable is represented by the signal intensity from each environment place, and the collection is made with equipment specific for this task. The idea of creating a signal coverage prediction is what inspired the development of models in this paper, where it is also proposed the use of statistic models applied to indoor environments.

Focused in models of RFID systems prediction, in [6], it is developed an ANN with retro-propagation for the detection interference of RFID tags close to water bottles. The scenario consists in an environment with a conveyor belt transporting a paper box with water bottles inside. The modeled neural network has one node on the output layer, which represents a logical value that informs if the tag was read or not. The prediction results had a minimal prediction percentage of around 70% and the maximum percentage coming close to 96%.

As a continuation of the previous paper, [7] presents a detection model for RFID tags using Support Vector Machines (SVM). In [7], it is analyzed the detection characteristics of the tags attached in paper boxes in a stationary environment. The model's objective is to predict the signal intensity of each tag attached to paper boxes. To measure the signal intensity, EPC Hotspot [8] software was used. The prediction results were obtained through comparison between the intensity value predicted and the value obtained in the real experiment, with the accuracy percentage being around 95%.

In [9], the same SVM method was applied to another typical RFID use case. In this scenario, the tags were attached to the front glass of a 1-ton truck and the antennas were placed in a portal (similar system used in tollbooths). The prediction results were obtained through comparison between the predicted tags detection and values obtained in the real experiment, with the accuracy percentage coming between 94.4 and 100%.

Each of these related papers has a distinct approach and contribute significantly to this research. Most of all, the publications of Nešković and Minho Jo provide support for the prediction models developed in this paper.

III. Environment (Testbed)

A typical RFID system use scenario can be found at the entrance of some environments that need to register the entry and exit of people, or even identify the individuals that are accessing the area. One way to carry out a system like that consists in attaching a passive UHF RFID tag to the person's badge. In these systems, an RFID reader antenna is placed on the side of the door, parallel to the wall. The adoption of a smart card is specially indicated to facilities like hospitals, hotel, schools, amusement parks, cruises, governmental buildings, as well as in events, ensuring more security and precision in access control and service performance. Recent researches also show the use of UHF RFID cards in public transportation systems [10].

A. Field experiments: design and implementation

During the experiments' design, two scenarios were prepared in a very realistic way to perform such experiments. The first scenario's goal is the execution of tests with the tag in movement (dynamic scenario), and in the second scenario, the experiments were made with the person standing in many different spots in the same environment (static scenario).

When using RFID smart cards, the factors that influence on RFID tags detection the most are: the material where the tag is attached; reader and tag model; tag orientation (vertical or horizontal); person's movement direction (entering or leaving the room); distance between reader and tag; reader transmission power; antenna gain; operation frequency; reader's antenna height; tag movement speed (in the dynamic scenario); number of tags in the environment; and the original characteristics from the environment. Original characteristics are influences such as room and door dimensions, walls' material and interfering objects, highlighting in this scenario the wall's material that is near the antenna and the door's height and width. Factors used on the field tests and its characteristics are described on Table 1.

For the factors that have fixed properties, the characteristics that most resembled typical environment cases presented in the beginning of this section were used. For example, the tag height related to the floor is the height of a badge used by a middle size person (1.75 m), the moving speed of the tag is similar to a person walking and the badge material usually is plastic. In the case "Number of objects tagged objects" there is a real world simplification. It is known that most of the time there are many people and tags simultaneously close to the reader.

TABLE I. FACTORS FOR BOTH SCENARIOS AND ITS CHARACTERISTICS

Factor		Characteristic
Tag	Material where it is attached	Plastic
	Object	Badge attached on an average size person (1.75m)
	Model	UPM Rafsec UHF DogBone 3000825
	Height related to the ground	1.25 m
	Moving speed	Dynamic scenario: 1.5 m/s
		Static scenario: stationary
	Orientation	Horizontal
	Direction	Variable
Reader	Model	Mercury 4
	Antenna	MTI MT-262010/TRH/A
	Antenna gain	8 dBi
	Antenna height	1.25 m
	Frequency	915.25 MHz
	Number of antennas	1
	Power	Variable
Environment	Number of tagged objects	1
	Distance between reader and tag	Variable
	Door's height x width	2.20 x 0.82 m
	Material (wall's material)	Variable (different rooms)

Taking into account the development of two scenarios and all the factors mentioned before, it was selected for each scenario the factors considered most important, defining them as the variables that influence the system's operation the most. Such variables will be the elements that define the proposed model of this paper. The definition of the variables and the measurement criteria are presented on Table 2.

TABLE II. VARIABLES AND CRITERIAS APPLIED TO MEASUREMENT

Factor	Dynamic	Static
Direction	Entering Leaving	Entering Leaving
Power (dBm)	Minimum: 24.5 Maximum: 32.5 Increment: 2	Minimum: 24.5 Maximum: 32.5 Increment: 1
Distance between reader and tag	0.40 m and 0.80 m	Ten spots according to Figure 1
Wall's material	Brickwork Glass	Brickwork Glass

The variable "direction" becomes important when determining whether the person is entering or leaving the room. The tag read count to a person entering the room can be different from the readings of a person who is leaving the room, since the person's body carrying the badge might be blocking the antenna transmission signal on different places for each option of the "direction" variable. In the direction "entering", the tag is directed to the interior of the room, while in the direction "leaving" the tag is directed to the external side of the room.

The reader's power is an important factor to be considered on an RFID system project. Passive tags receive energy coming from the reader, therefore the intensity of this energy depends directly on the reader power configuration. Because of that, a low power will not provide enough energy to active the tag, or in case it is activated, the tag might not have enough power to backscatter the information to the reader. On the other hand, a high power can generate more reflections and readings in locations outside the area of interest. It is important to highlight that the maximum power might be conditioned to the laws of the country or region.

For the "distance" variable, there are distinct situations for both projected scenarios. In the dynamic scenario this variable is considering the distance from the moment that the person crosses in front of the antenna. In the static scenario the tag has its static position defined by ten spots in the environment; as it is presented in the Figure 1. In this case the distance variable might be represented using the information of the distance X and Y of each spot on the 2D map.

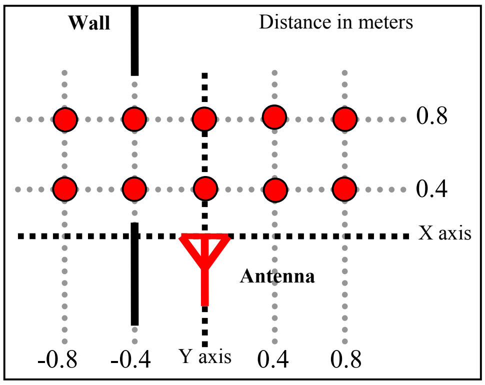

Figure 1. 2D level of the tests. The ellipses represent the person's position on the static scenario.

The variable "material" represents the wall's composition from both places where the experiments will be made: a room with brick walls and another with glass walls. The RF wave propagation in closed environments depends incisively on any electrical conductive object whose physical dimensions are greater than ¼ of the wavelength. This way, the propagation is related to parameters like the room geometry and the walls and furnishings' material. The dielectric material properties from a given room define the transmission and reflection characteristics, consequently affecting the radio wave propagation in indoor environments. Different materials have distinct transmission and reflection coefficients. This way, a radio wave propagation through a metallic wall will be more attenuated compared to a wave passing through a brick wall [11] [12] [13].

Having all variables defined, it can be concluded that the dynamic scenario has four variables, with the "direction" variable having two possible values, the "power" variable five values, the "distance" variable two values and the "material" two options. As such, there are 40 distinct situations (2 x 5 x 2 x 2 = 40). The data collection experiments used on the statistic model should contemplate all the 40 situations, and to achieve more precision on the results, each situation needs to perform five experiments repetitions. Therefore the data collection on the moving scenario needs a total of 200 experiments (40 x 5 = 200).

The static scenario has also four variables, having the "direction" variable two values, the "power" variable nine values, the "distance" variable ten positions and the "material" variable two options. Thus, there are 360 distinct situations (2 x 9 x 10 x 2 = 360). For each situation it also will be run five experiments repetitions, resulting in a total of 1800 experiments (360 x 5 = 1800) on the static scenario.

On the dynamic scenario the read count will be measured in a three meters perimeter, while on the static scenario each experiment will activate the reader during five seconds, storing the tag read count collected on this period.

B. Collected data analysis

The experiments execution on both projected scenarios resulted in an information database about the amount of readings made in each experiment. The dynamic scenario had a read count between 0 and 25, while the static scenario had a reading range between 0 and 96. In a brief analysis it was observed that the environment configuration that led a better communication had a greater read count, while worse configurations (such as a low reader power scenario) usually resulted in a lower number of readings. This confirms that the tag read count is a good variable for predicting RFID systems coverage, which can indicate suitable locations and settings for deployment.

Statistically analyzing the collected data, it was found that even isolating many characteristics that might interfere on the tag reading (such as exact devices positioning, furniture or other interfering objects removal, etc), the number of readings for each given situation varies between repetitions. This read count distribution happens mainly because of factors: (i) the high sensitivity of RFID system devices; (ii) variables still unknown that might influence in the system.

Given the variance in the number of readings, a method for exclusion of samples that have gross measurement errors was sought. The Quartis Method was applied in the experiments database made on both scenarios. The final database of the dynamic scenario resulted in a total of 193 records and the static scenario had a total of 1757 records.

IV. Proposed Approaches

A. Linear Regression

In order to obtain a prediction model using the experiments database, we decided initially to use one of the most basic statistical inference approach: linear regression.

In linear regression is not possible to work with nominal values, i.e. values that do not have a numeric scale defined. In the scenarios specified in this work there are two nominal variables: material and direction. Thus, the regression model obtained from a multiple linear regression is applied only to the power and distance, and each combination of material and direction has distinct equations. Based on the general equation of multiple linear regression, the model for the dynamic scenario was developed as follows:

$$L(p,x,y) = m_{pi} \cdot p + m_{di} \cdot d + b_i \quad (1)$$

where L is the predicted read count, p is the power in dBm and d is the distance (in meters) between the reader antenna and the tag. In (1), for each case (i) of material and direction, it is required a distinct coefficient which multiplies the power (m_{pi}), another to multiply the distance (m_{di}), and also the linear regression coefficient (b_i). In the stationary scenario, the inference model is quite similar to (1), with the difference that there are two distance coefficients (x and y), instead of just one (m_{di}).

In order to apply the experiments database in linear regression, initially it was calculated the reading average for each distinct combination of material, direction, distance and power. The reading average was necessary since each combination has five records in the database, as mentioned in section III.A.

After running the linear regression analysis in IBM SPSS Statistics, we get an R^2 between 0.7 and 0.92 for the dynamic scenario and an R^2 much lower than 1 for the static scenario. Analyzing the prediction error, the mobile scenario has also a better performance than the static scenario. The standard error for dynamic scenario established between 1 and 4 reads, while the static scenario has an error above 20 reads. The statistical results show that static scenario has a nonlinearity on the set data, proving that the linear regression model is not suitable for obtaining a good prediction.

Analyzing the low performance in the R^2, mostly in the static scenario, we decided to use another statistical method to improve the performance in both scenarios.

B. Artificial Neural Network (ANN)

Feedforward neural networks with sigmoidal activation functions have shown very good performance in solving problems with mild nonlinearity on the set of noisy data [1].

1) Dynamic scenario

A feedforward neural network with 6 inputs and one output was designed. The first input has the distance between the reader antenna and the tag, while the second input receives the power of the reader, inputs 3 and 4 represent the both directions (entering and leaving the room) and the inputs 5 and 6 stand for the wall material. This model was concluded with four nodes in the hidden layer. The output node presents the final result, defined in this work as the read count of the tag for the specified input combination. The activation function used in all layers was the sigmoidal.

The ANN model was simulated using IBM SPSS Statistics. In the ANN training, all information collected in the experiments was used. The ANN parameters for the training are: (i) Training dataset: all data collected. (ii) Training mode: batch; (iii) Learning algorithm: Scaled Conjugated Gradient. (iv) Stop criteria: relative error in 0.0001. Attempts were made to change hidden layers and the learning algorithm, but it had not led to better performance.

a) Results

Initially, the ANN model was trained using data of each experiment repetition. However, the training had a RMSE of 1.631, which is a value above the expected. Thus, we decided to use the average of read count as output value for each distinct situation. So, the samples for the training were reduced from 193 to 40, which is the number of distinct cases we have in this scenario. The training was performed again and the RMSE was 0.039.

In order to present the results of read count of the tag in the environment, the read count prediction for the dynamic scenario was performed using a distance resolution of 0.1 m and power step of 1 dBm. The distance range was limited in 0.1 and 1 m and the power between 24.5 and 32.5 dBm. Figure 2 shows graphs of read count coverage predicted by the ANN model designed.

In Figure 2, both top graphs show results for brickwork material and the bottom graphs show results for glass. Analyzing the gradient in the graphs, obtained for each distance, we can see a good convergence of the number of readings in relation to power (X-axis), proving that the higher the power is, the higher is the read count. Focusing on the distance variable, some situations have an unexpected behavior, like brickwork material, and the "entering" direction, where there are higher read count in close distances, lesser in intermediary distances (between 0.4 and 0.7 m), followed by higher readings in farthest spots.

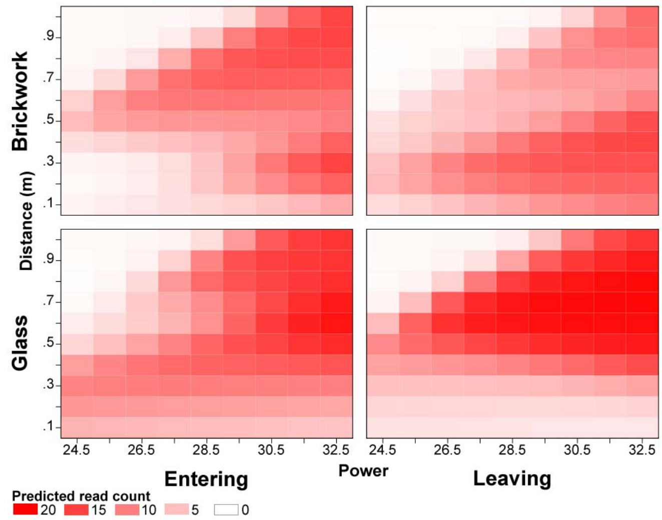

Figure 2. RNA results for dynamic scenario

Analyzing the system's behavior in relation to wall materials, the material "glass" had, in some powers and distances, a higher read count than brickwork. Also, it's noted that the direction "leaving" has better coverage, both in the distance and power analysis. Likely, in this direction, the tag a person is carrying the card in stays more time inside the room, having the tag aimed to the reader's antenna.

b) Validation

The model developed was validated using a dataset collected in new experiments. In the first validation phase, tests were performed in a new environment, similar to the first set of experiments. In the second phase, validation experiments had new distances and power values, i.e., different values from former experiments. Being so, the ANN was validated using values never known by the model.

In the second phase, the distance 0.6 m and power 25.5, 27.5, 29.5 and 30.5 dBm were included to the dataset. This dataset results in 36 samples for validation, being 20 in the first phase and 16 in the phase two.

In the validation results analysis, one must take into account the fact that it is not possible to perform a direct comparison between the original and predicted values, because for certain situations, the read count changes from one repetition to other.

In researches about prediction of field strength level, where measured field levels are compared to predicted values, the average and standard deviation of validation errors are presented [1]. Due to the similarity of this model with the RF models, we decided to use a same approach when presenting this model's accuracy.

In order to obtain the average and the standard deviation of errors, we calculated the absolute error of each validation test. The absolute error is defined as $e = | r_m - r_p |$,where r_m is the tag read count measured in validation experiments and r_p is the predicted read count from ANN model. Table 3 shows the results of average and standard deviation prediction errors.

TABLE III. DIFFERENCE BETWEEN PREDICTED VALUE AND MEASURED VALUE IN MODEL VALIDATION (DYNAMIC SCENARIO)

	Entering		Leaving	
	Avg.	*Std. dev.*	*Avg.*	*Std. dev.*
Brickwork	2.5	1.8	4.0	3.3
Glass	5.8	4.5	7.0	4.1
Avg.	3.9			
Std. dev.	3.33			

No minimum error for the read count prediction in an RFID system is known. Thus, we decided to take into account that the read count range from first experiments is between 0 and 25 (section III.B), the standard deviation of the errors (3,33) represents 13% of the maximum read count value.

2) Static scenario

The model design for the static scenario had few differences from the dynamic scenario model, due to the fact that a feedforward neural network was also developed. One difference is the input layer, defined with seven inputs. Inputs 1 and 2 represent the distances between the reader antenna and the tag, where input 1 has the horizontal distance in 2D plane (X axis) and input 2 has the vertical distance (Y axis). Input 3 considers the reader power, inputs 4 and 5 represent both directions and inputs 6 and 7 stand for the wall material. This model was concluded with four nodes in the first hidden layer, three nodes in the second hidden layer and one node in the output layer. On this model, the output node also represents the tag read count for the input combination (distances, power, direction and material). The activation function used in all layers was the sigmoidal.

a) Results

The ANN model was simulated using the same parameters of dynamic scenario model. The training using data from each experiment repetition also had a unsatisfying result, with a RMSE of 30.174. Thus, we decided to use the read count average for each situation, resulting in 360 samples. In the end of this training the RMSE decreased to 0.733.

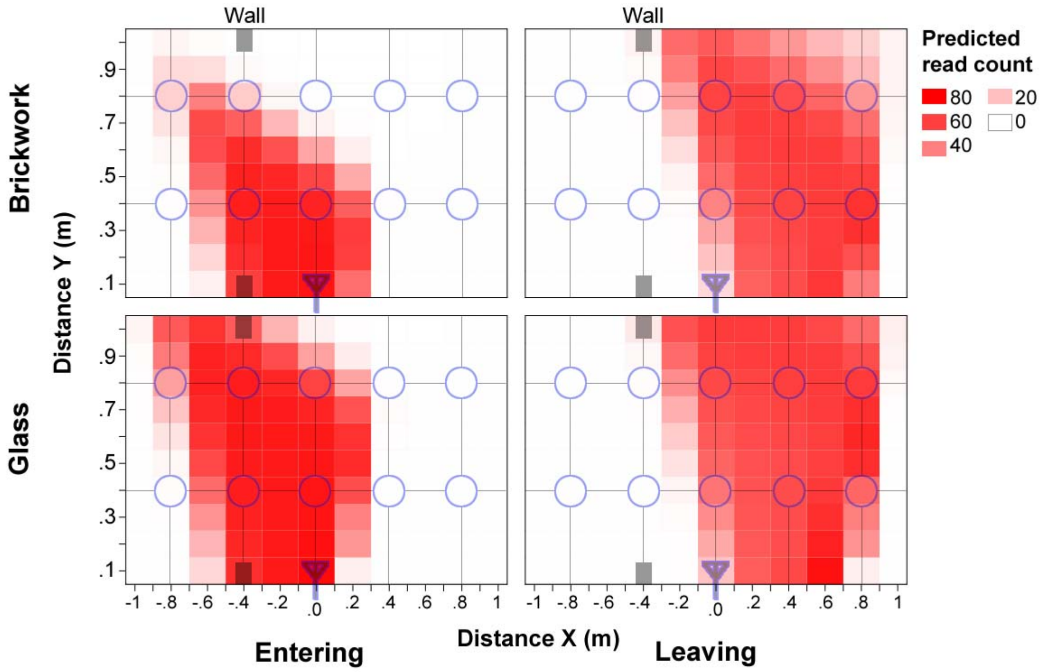

Figure 3. Predicted read count coverage applied to static scenario (power: 30 dBm).

After the ANN model training, a dataset for the read count prediction was built, containing values which have never been used in training. The dataset has the information of both materials and directions. It was used a distance resolution of 0.1 m and a power increment of 0.5 dBm. The coverage was limited to 2 m in X axis and to 1 m in the Y axis, according to 2D plane of the environment. The ANN model prediction resulted in a dataset containing the tag read count in all environment spots for every material, direction and power combinations. Figure 3 graphs show the read count coverage predicted by the ANN model (power: 30 dBm). Ten ellipsis of each graph represent the positions where the values were measured in the previous experiments.

In Figure 3, the graphs show the outdoor and indoor coverage of read count prediction. Analyzing the results for direction "entering", we realize that the read coverage has good performance, "leaking" some readings outside the room and concentrating more readings near the door and the antenna. Also, in the direction "entering" there are no readings in distances above 0.2 m (X axis), due to the fact that the person using the card is back facing towards the antenna, covering the tag component.

The direction "leaving" shows a read count coverage where there is no outdoor communication between the reader and the tag. It happens because while outside, the tag is covered by the persons' body. Analyzing the effects inside the room, the read coverage in the direction "leaving" is almost complete, where the farthest spots (X axis and Y axis) have a read count below the spots close to the antenna.

Still analyzing the results from Figure 3, in the comparison between "brickwork" and "glass" materials, it is noticed that there are a few differences in the read count coverage. In some cases of the direction "entering", the material "brickwork" has fewer readings than material "glass".

b) Validation

As with the dynamic scenario, the first validation phase has an environment with characteristics like the first experiments. In the second validation phase, we performed experiments with new distances and power values. The new vertical (Y axis) distance is 0.6 m. In the horizontal axis we validated the distances -0.6, -0.2, 0.2, 0.4 m. In this validation process we also have the new power values of 25, 26, 27, 28, 29, 30, 31 and 32 dBm.

308 samples in the validation were collected, 180 being in the first phase and 128 in phase two. From the dataset collected, it was performed the comparison between the read count from validation and the values predicted by the model. Table 4 shows results of average and standard deviation prediction errors, calculated in the same way of the dynamic scenario validation.

TABLE IV. DIFFERENCE BETWEEN PREDICTED VALUE AND MEASURED VALUE IN MODEL VALIDATION (STATIC SCENARIO)

	Entering		Leaving	
	Avg.	*Std. dev.*	*Avg.*	*Std. dev.*
Brickwork	14.1	25.1	15.0	16.4
Glass	14.7	23.7	20.3	16.0
Avg.	15.2			
Std. dev.	21.0			

The validation results in this model show an average and standard deviation that's above the expected. Taking into account the read count range of 0 and 96 (section III.B), the general standard deviation (21) represents 22% of the maximum read count. Devices' high sensitivity and external variables effects could be the main reason for errors detected in validation. Bearing in mind that in the validation experiments, the read count also varied from one experiment repetition to another, even using the same environment variables and system configuration.

V. Conclusion

This paper presented site-specific prediction models for RFID systems. The first model used a method called Multiple Linear Regression. Both other models used Artificial Neural Networks, being applied in dynamic and static scenarios.

During the experiments it was detected a great variance of the reading count between the tests repetition with the same environment configuration. Nevertheless, the models developed were capable of predicting the configurations that provided the best and worst readings, i.e. the best and worst communication results between devices. The interference results from the models proved that the number of readings increases as the reader equipment power is increased. It was not detected any relevant behavior difference related to the wall's material of the room where the experiments were made.

The tag position is also an important factor in the read count, resulting in a different communication in certain environment places. The difference in read count due to the components' position is motivated by the effects of countless maximum or minimum values of signals distributed through the covered area. Such effects happen from the constructive or destructive interference of many reflected waves on the operation scenario. This is a fact that was not considered in this research and should be analyzed in future works.

The models validations were made through new field experiments, where the models obtained a relatively low error rate in the dynamic scenario and a high error rate in some cases in the static scenario. Most of the cases, such errors are acceptable if the existing variance during the data collection experiments is considered, where factors like high sensitivity of the devices and external variables that were not considered might impact on the values of the measured samples.

Unfortunately, a direct comparison to results of previous researches is not possible, because the result metrics applied in this paper differ from those works. This work focus on tag reading intensity as result metric, while those are based on a "hit or miss" approach. It is not known in literature a RFID systems prediction based on tag reading intensity.

A. Future Work

During the necessary experiments by the statistic models, it was confirmed the influence of other environment factors that were not considered on the experiments project. Such factors can cause significant impact on RFID systems. One of the factors witnessed during the tests might have relation with the luminosity level in the environment. A detailed work where all the others environment variables are isolated, might check the variance impact of this characteristics on the operation of RFID systems.

The methodology developed in order to generate the models is not restricted to the smart cards scenario. It also can be applied to other typical RFID scenarios, such as conveyor belts or pallets carrying boxes that have RFID tags.

A variable that is not included in the proposed work pertains to the number of tags on the environment. An RFID system working with more than one tag may have a different behavior in the physical layer when compared to a system where there is only one tag. In a system with many tags acting simultaneously, it is also necessary to mind the message collision problem in the logical layer.

References

[1] Nešković, A.; Nešković, N.; Paunović, Đ. "Indoor electric field level prediction model based on the Artificial Neural Networks", IEEE Communications Letters, vol. 4-6, Jun 2000, pp. 190-192.

[2] Nikitin, P.; Rao, K. "Antennas and propagation in UHF RFID systems". In: IEEE International Conference on RFID, 2008, pp. 277-288.

[3] Jain, A.; Agarwal, S.; Jagannatha, S. K.; Narayanaswamy, G.; Engels, D. W. "Performance analysis of alien squiggle tag in human presence". In: Antennas and Propagation Society International Symposium (APSURSI), 2010, pp. 1-4.

[4] Alien Technology. "Alien Technology - Products - RFID Tags". http://www.alientechnology.com/tags, visited on october, 2011.

[5] Floerkemeier, C.; Sarma, S. "RFIDSim - A physical and logical layer simulation engine for passive RFID", IEEE Transactions on Automation Science and Engineering, vol. 6-1, Jan 2009, pp. 33-43.

[6] Jo, M.; Lim, C.; Zimmers, E. W. "RFID tag detection on a water content using a back-propagation learning machine", KSII Transactions on Internet and Information Systems, vol. 1-1, Dez 2007, pp. 19-32.

[7] Jo, M.; Youn, H. Y.; Chen, H. "Intelligent RFID tag detection using Support Vector Machine", IEEE Transactions on Wireless Communications, vol. 8-10, Out 2009, pp. 5050-5059.

[8] QTrac. "QTrac - RFID Solutions". http://www.qtrac.com/Solutions_Hotspot.asp, visited on october, 2011.

[9] Jo, M.; Youn, H. Y.; Cha, S.; Choo, H. "Mobile RFID tag detection influence factors and prediction of tag detectability", IEEE Sensors Journal, vol. 9-2, Fev 2009, pp. 112-119.

[10] Oberli, C.; Landau, D. "Performance evaluation of UHF RFID technologies for real-time passenger tracking in intelligent public transportation systems". In: IEEE International Symposium on Wireless Communication Systems, 2008, pp. 108-112.

[11] Rappaport, T. S.; Sandhu, S. "Radio-wave propagation for emerging wireless personal-communication systems", IEEE Antennas and Propagation Magazine, vol. 36-5, Out 1994, pp. 14-24.

[12] Schafer, T. M.; Maurer, J.; Hagen, J.; Wiesbeck, W. "Experimental characterization of radio wave propagation in hospitals", IEEE Transactions on Electromagnetic Compatibility, vol. 47-2, Mai 2005, pp. 304-311.

[13] Zhang, J. T.; Huang, Y. "Investigation of building dielectric properties and the effects on indoor radio channel". In: Twelfth International Conference on Antennas & Propagation (ICAP), 2003, pp. 207-211.