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Optimization of Antenna Coupling through Machine Learning for "Smart" TPMS Readers

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Abstract

Tire pressure monitoring system (TPMS) is becoming ubiquitous in modern day vehicles with advanced safety and driver assist systems and plays a key role in predictive maintenance. One of the key challenges to realize an efficient TPMS system is to ensure good antenna coupling between the reader antenna in the cabin or on the roof of the vehicle and the antennas in the tires. Understanding the different external factors that affect the antenna coupling is vital to realize an efficient design. Computer aided simulations on antenna coupling is a cost-effective method to reduce the chances of failure before a TPMS is deployed in an actual vehicle. In this work, a computational approach is presented to optimize the antenna coupling and hence the link budget between the reader antennas and the TPMS antennas at 915 MHz. This is achieved by employing machine learning based optimization using commercially available tools, Altair's HyperStudy and Altair's Feko. A powerful combination of machine learning technique (regression-based mathematical modelling) to develop a surrogate mathematical model coupled with Global Response Search Method (GRSM) optimization is demonstrated for achieving the goals with very few design iterations A case study is presented that demonstrates the workflow process of optimizing the TPMS antenna coupling using body in white of an automobile. A comparison is also shown between traditional GRSM reader antenna position optimization and optimization coupled with machine learning showcasing significant reduction in computational time and memory.

Introduction

Internet of things (IoT) has found deeper inroads into automotive industry providing wireless sensing solutions for various applications that enable safe operation of vehicles [1]. One such solution is the wireless Tire pressure monitoring system (TPMS) that plays a key role in determining the quality of tires and serves as an important indicator for predictive maintenance. A typical TPMS consists of a pressure sensor with an antenna mounted on each of the tires and a receiver antenna located inside the vehicle cabin or on the roof of the vehicle for communication [2, 3]. The sensor coupled with the antenna is responsible for determining the pressure of the tire and to transmit this information to the reader along with an identification information. The principle is similar to that of a typical Radio Frequency Identification (RFID) system as illustrated in Figure 1.

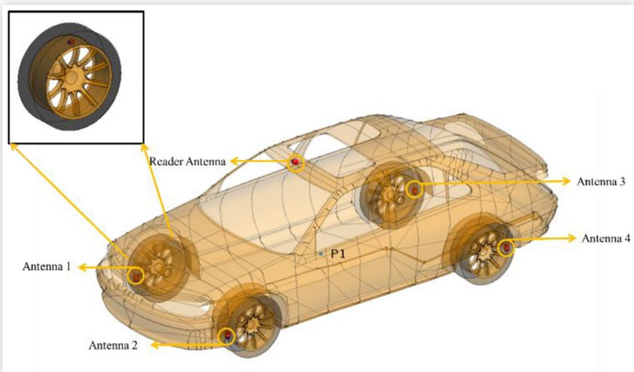
A key challenge for a good TPMS design is to determine the position of the receiver antenna on the vehicle for optimal coverage of all the four tire sensors. An example schematic of the vehicle with four TPMS antennas in the tires and a reader antenna on the roof is shown in Figure 2.

Traditionally, optimal planning of the coverage is a difficult task that requires careful consideration of all the factors that affect the antenna coupling such as vehicle metal body, tire geometry, material of the tire, as well as antenna parameters such as polarization, gain at the frequency of operation, and link budget between the antenna and the reader [3]. For a typical two antenna system separated by a distance, d in free space, the maximum power transfer from antenna 1 to antenna 2 is defined by equation (1). This is under the assumption that the matching network is ideal, and the antennas are aligned for maximum directional radiation and reception in free space.

$$P_2 = \frac{P_1 G_1 G_2 \lambda^2}{(4\pi d)^2} \tag{1}$$

FIGURE 1 Example of a generic wireless Tire Pressure Monitoring System.

FIGURE 2 3D Schematic of the physical model (body in white) with four antennas on the tires (TPMS sensor antennas) and the reader antenna on the roof.



P_2 is the received power at antenna 2, P_1 is the total transmitted power from antenna 1, G_1, G_2 are antenna 1 and antenna 2 gains, respectively, λ is the wavelength, and d is the distance between the antennas [3]. For the case of TPMS, consider the TPMS sensor antenna and the reader antenna as a two port system, it is sufficient to compute the scattering parameters (S-parameters) and in particular the transmission parameters (S_{mn}) to determine the best optimal distance (d) for coverage planning. The S-parameters provide the quality of transmission and reception between a pair of antennas including the external effects mentioned earlier such as the metal body, tire geometry and material, and other surrounding environmental factors. So, maximizing the transmission coefficient is normally chosen as the key optimization goal to achieve good coupling coefficients between the reader antenna and the antennas on all four tires.

There are numerous optimization techniques available in literature and can be easily applied to computer aided simulation for the antenna coupling optimization. But these techniques are limited due to the requirement of multiple simulation iterations to complete the optimization process that could be expensive in computational time and memory. In order to overcome this, recently, there is a growing trend to apply machine learning techniques to perform "intelligent" optimization with less computational cost [4]. Conventionally, machine learning (ML) has been extensively used in industries for analyzing large amount of data for multiple applications such as financial market analysis, traffic pattern analysis, retail and shopper pattern analysis, healthcare and personalized health analysis and many more applications [5]. A similar trend is catching up in utilizing machine learning principles for Computer Aided Engineering (CAE) and in particular Computer Aided Electromagnetics Design. Machine Learning provides an additional degree of freedom for the design engineers as optimization using machine learning allows analyzing multiple scenarios without investing more time and additional computational resources.

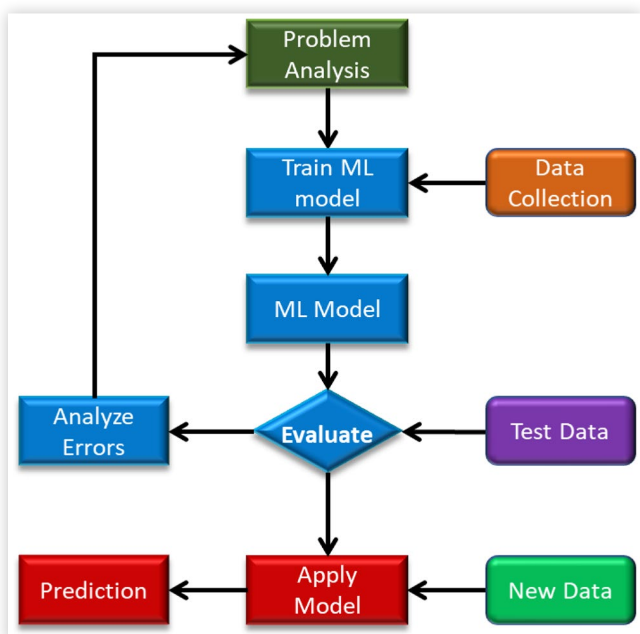
In this paper, a case study is presented showcasing machine learning techniques for optimizing antenna coupling between the reader and the tire antennas of a vehicle. A trained mathematical model is generated using Altair HyperStudy [7, 9], a multi-disciplinary design exploration and optimization software and numerical electromagnetics simulations are performed using high frequency electromagnetics solver Altair Feko [8]. The paper is organized into the following sections, first, machine learning methods are introduced, second a typical workflow for antenna coupling analysis using machine learning optimization approaches is presented, and finally, a case study is presented for coupling and position optimization of the TPMS reader antennas using machine learning. A comparison is also presented between the coupling coefficients of the reader with the tire antennas for the predicted reader antenna position using machine learning optimization as well as regular optimization.

Machine Learning Techniques

Machine learning techniques are devised to express a physical model as an analytical model in terms of mathematical expressions. The mathematical model contains a number of parameters that can be optimized to achieve an objective for the model [6]. In order to generate a mathematical model, first, the machine should learn from the available data by employing a data collection technique to extract data from the physical model. Once the mathematical model is created from the training data, it is evaluated using a standard set of test data. If the model is validated, then a new set of data can be applied to it to predict the best optimal outcome without the need of the physical model. A typical workflow for a machine learning algorithm is presented in Figure 3.

Most commonly, machine learning can be classified into unsupervised and supervised learning primarily based on the method of data collection for generating a mathematical model. In case of unsupervised learning, large amount of data is collected without any pre-existing constraints and is analyzed to find a particular trend or useful structure in the

FIGURE 3 Example of a machine learning algorithm.



data. For supervised learning, a set of pre-defined boundaries or reference points in the analytical model is available and the data is generated based on such boundaries. The algorithm uses the sampled data to generate a mathematical model. For example, data is generated by running antenna simulations based on pre-defined boundaries for different parameters in the antenna model and analyzed for behavior of the model. In this work, a supervised machine learning approach is used for generating the trained model. Furthermore, there are two major categories of supervised learning, classification and regression. Without loss of generality, classification predicts the type of data and tries to classify data based on categories whereas regression predicts a numerical value based on previously obtained data. This work is focused on using regression method for generating a trained mathematical model.

Regression Method - Data Collection

Regression method enables prediction of continuous output based on one or more design inputs. Consider the following equation (2)

$$Y = f\left(X_n\right) \tag{2}$$

Where, X_n stands for n-dimensional input variable or design or predictor variable and Y stands for continuous output variable. The regression model maps Y as a function of values of x through a fixed but unknown function f. There exist multiple regression approaches to predict continuous output Y such as Least Square Regression, Moving Least Square Method (MLSM), and Radical Basis Function (RBF). The application of regression methods for generating a machine learning based model has many-fold advantages as it accelerates the process of optimization in comparison to using the actual physical simulation model. The data on which the regression method is applied to create a trained model is generated by Design of Experiment (DoE) methods.

Design of Experiments

Design of experiments is a series of simulation runs that are used to generate the required data to train the mathematical model. It also aids in understanding the overall impact of various input parameters in realizing the desired outcomes. The input variables are varied based on a pre-defined bound and the effect on the output is collected as data generated for the machine learning model. The pre-defined bound is generated based on the type of the DoE method. There are two major types of DoE methods, a screening method, and a space filling method. The screening method is predominantly used to elucidate most influential input variables based on the output responses. Most common screening methods are Taguchi, full factorial, fractional factorial, and Plackett Burman. The screening method often requires more samples than the space filling method to extract the influential variables. The space filling methods cover the design space efficiently by sampling a series of evenly distributed input variables while minimizing the number of runs to develop a trained surrogate model in place of a physical model. Examples of space filling techniques are D-optimal, Central Composite Design, Hammersley, Box Behnken, Lattin Hypercube, and Modified Extensible Lattice Sequence (Mels). In this work, Mels is used as a space filling DoE method to obtain the data for generating the machine learned electromagnetics simulation model. Mels is a quasi-random sequence designed to equally spread out points in space minimizing clumps and empty spaces. Further details on Mels can be found in [7,9].

Antenna Coupling Optimization Using Machine Learning

In this paper, a typical workflow for optimizing antenna coupling analysis using machine learning is presented using a combination of Altair's HyperStudy and Altair's Feko. To begin the process, a parametric model of the physical model (reader antenna position parameterized along x-axis and y-axis with a fixed z-axis) is built in Feko and is imported into HyperStudy along with the design variables. A new study is setup where DoE is used for data collection from the parametric model. Once the data collection is completed, a machine learning mathematical model is generated by HyperStudy and trained using the collected data. After the training, optimization is performed on the trained machine learned model using optimization methods (GRSM method) available in HyperStudy to achieve the desired outcomes. A typical workflow is presented in Figure 4

In case of antenna coupling, as mentioned earlier, optimization is performed by maximizing the transmission coefficient (coupling coefficient) between the reader antenna and the tire

FIGURE 4 A typical workflow for running ML based optimization for electromagnetics components using Altair's Feko and Altair's HyperStudy.

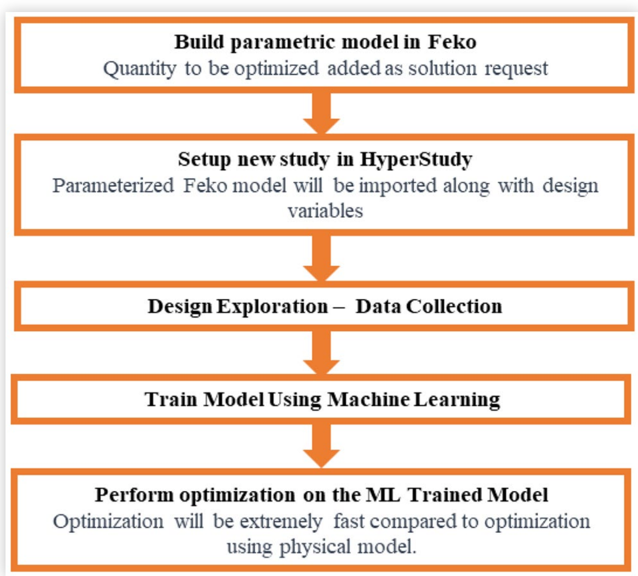
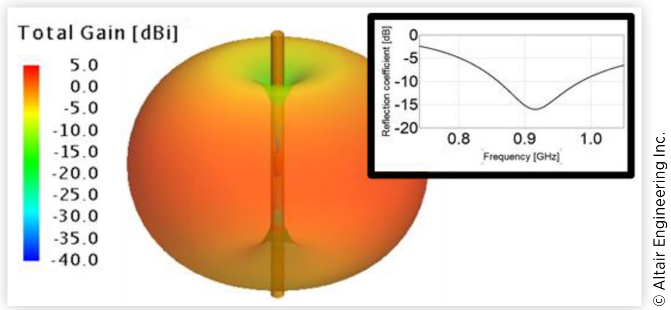


FIGURE 5 3D Radiation pattern of the dipole antenna at 915 MHz with reflection coefficient (inset).



antennas. The goal is achieved by optimizing the position of the reader antenna on the vehicle cabin such that all the four tire antennas have the best possible coupling with the reader antenna. A case study to illustrate this workflow process is presented in the next section. For the case study, a generic dipole antenna model is used for representing both the reader and the tire antennas. FCC approved RFID frequency 915 MHz is chosen as the frequency of operation for all the antennas. The dipole antenna was designed using Feko's Method of Moments Solver. Figure 5 shows the schematic with the 3D radiation pattern and reflection coefficient of the dipole antenna.

Case Study: Position Optimization of TPMS Reader Antenna Using Machine Learning

A generic automobile was chosen with TPMS antennas located inside the four wheels and the reader antenna on the front roof panel (Figure 2). The position of the reader antenna was parameterized to be fed into HyperStudy for generating a trained mathematical model. The body in white of the vehicle is used in this demonstration. Perfect electric conductor (PEC) is assigned to the sheet metal to represent the metallic vehicle body effects while calculating the antenna coupling. Furthermore, the rim of the tires and the top face of the tires are also assigned PEC and the material face of the tires assigned the properties of a dielectric with ϵ_r of 5 and $\tan\delta$ of 0.01. The inside of the tire is filled with air ϵ_r of 1 and the TPMS antennas are fixed at certain pre-defined locations inside the air region of the tire. The reader antenna is placed at a certain position ($x_{start}, y_{start}, z_{start}$) on the front roof panel. An allowed real-estate for the reader antenna to be positioned on the front panel is defined as parameters with bounds along the x and y direction (fixed z direction). The vehicle body and the tires are solved using Feko's asymptotic solver, Ray Launching Geometrical Optics (RL-GO) and the antennas are solved using Feko's full wave solver Method of Moments (MoM). For the demonstration of this example, the position is parameterized such that any point can be chosen from a sample space of x and y and applied as the position of the reader antenna ($x_{start} + x, y_{start} + y, z_{start}$). The sample space of x is bounded by $\pm 0.3\ m$ or [-0.3,0.3] and y is bounded by $\pm 0.04\ m$ or [-0.04,0.04]. The four tire antennas are placed on tires at the farthest practically possible distance from the reader antenna. The front tires have the antennas oriented at the center (left of the tire rim) of the tire and orthogonal to the reader antenna. The rear tires have the antennas oriented at the center (right of the tire rim) of the tire and orthogonal to the reader antenna as shown in Figure 2.

Data Collection

The first step after setting up the study in HyperStudy is to collect data using space filling algorithm such as Mels from the physical model by running several iterations of the x and y sample space. In this data collection step, Mels took only 7 iterations to collect the data from the physical model. Figure 6 shows the influence of the variable parameters x (position of the reader along x-axis) and y (position of the reader along y-axis) over the transmission coefficient of all four tire antennas. It can be inferred from the plot that the coupling between the antenna and the reader for both the front and the rear tire antennas (all four) is significantly influenced by the movement of the reader along the x-direction in comparison to the y- direction.

Machine Learning Model

The data collected from the design exploration phase is used to generate a trained machine learning model using Altair's proprietary regression algorithm Fit Automatically Selected by Training (FAST) in HyperStudy. If an excellent correlation has been achieved between the physical model and the trained model, then the objective of generating a machine learning model is successful. Figure 7 shows the correlation between the physical model and the ML model for antenna coupling between the reader antenna and tire antennas (1 through 4).

From Figure 7, it can be inferred that a linear relationship exist between the physical model and the ML model for all four antennas. This implied that the ML mathematical model

FIGURE 6 Influence of positions along x & y axes for the reader antenna over the transmission coefficients of each of the tire antennas.

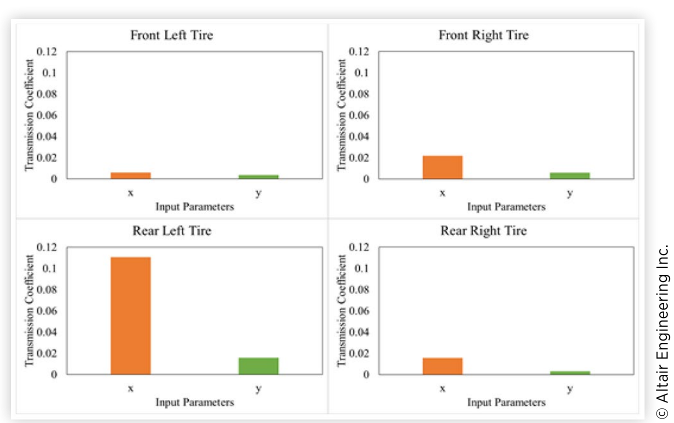
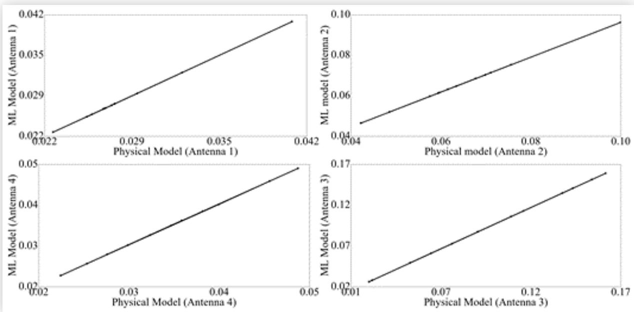


FIGURE 7 Correlation between the physical model and the trained machine learned model for coupling between the reader antenna and tires antennas 1 through 4 (clockwise).



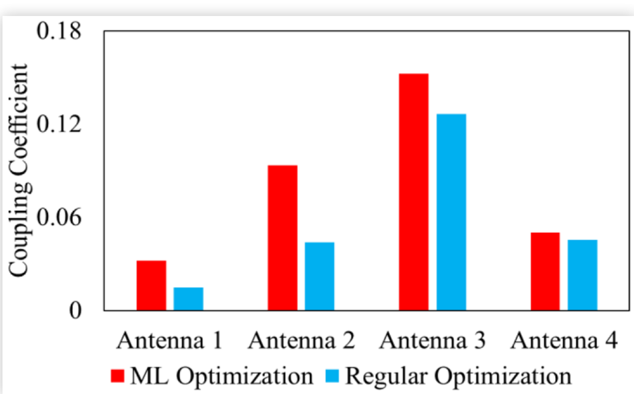
obtained after being trained by the collected data is a very accurate and excellent mathematical representation of the physical model. So, the mathematical model can be used in place of the physical model for further optimization.

Optimization Using ML Model

The next step is to perform optimization for a specific goal, in this case, maximizing the transmission coefficient (coupling) by using the mathematical model instead of the physical model. This allows accelerated design cycle since it takes only few seconds to generate the optimized model from the mathematical model or ML model. A Global Response Search Method (GRSM) optimization on reader position is performed to obtain best coupling between all the four tire antennas and the reader antenna at 915 MHz. For comparison, reader antenna position optimization is also performed using physical model in Feko using the GRSM optimizer (regular optimization). Figure 8 shows the comparison between the coupling coefficient of all four antennas with the reader antenna at the optimized reader antenna position on the roof for both ML and regular routine.

It can be inferred from Figure 8 that the reader antenna position optimized using the machine learning model has better coupling strength between all four antennas in comparison with the reader antenna position optimized using Feko (Regular optimization). Optimization using machine learning took 15 mins of CPU time for data collection using Mels and a few more seconds for generating trained ML model as well as 50 iterations of optimization of the trained ML model., whereas, optimization using using Feko took 98 minutes of CPU time for 50 iterations. This shows that ML based optimization is a powerful and efficient optimization technique that generates better results in a very short period of time, to be precise, 6 times lesser than the regular optimization and with reduced computational resources.

FIGURE 8 Comparison between antenna coupling coefficients for optimized reader antenna position on the roof using ML based optimization and regular optimization routines.

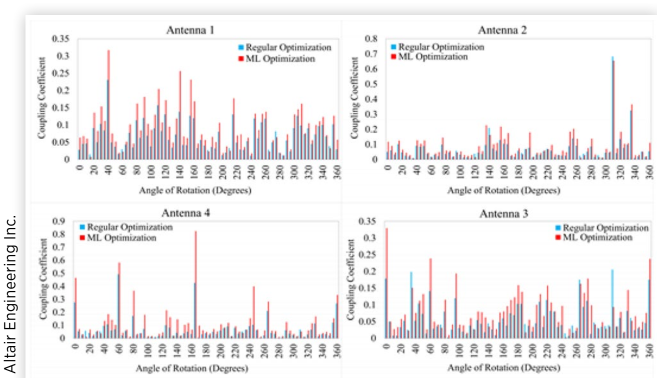


Antenna Coupling with Rotation

In order to further validate the optimization process, another set of Feko simulations are performed by adding another dimension of complexity, the rotation of all four tires which in turn rotates the antennas as well. For the purpose of simulation, the final optimized reader antenna position on the roof of the vehicle for both regular optimization and ML optimization is fixed to the positions predicted by respective routines. For both cases, all four wheels are simultaneously rotated from 0 to 360 degrees with an increment of 5 degrees. The coupling coefficient for all four tire antennas with the reader antenna on the roof of the vehicle is computed and plotted for comparison in Figure 9.

It can be inferred from Figure 9 that the position of the reader optimized by ML routine shows better coupling coefficients for most cases of tire rotation than the position of the reader optimized by the regular routine. This shows that ML not only reduces consumption of resources and time but also generates excellent surrogate mathematical models that allows better achievement of optimization goals with very few iterations and in shorter time. Further studies can also be performed including a goal that specifies a baseline coupling coefficient value required at all angles for the tire rotation to realize an efficient design.

FIGURE 9 Comparison between the coupling coefficients for both the ML optimized and regular optimized reader antenna position with tire rotation included. Antennas 1 through 4 (clockwise).



Summary/Conclusions

In this work, a systematic approach for optimization of antenna coupling for TPMS system using machine learning is demonstrated using a combination of Altair's high frequency solver Feko and multi-disciplinary optimization and machine learning tool Altair HyperStudy. The case study presented showcases the applicability of Mels algorithm for data collection and generation of the mathematical model using supervised learning algorithm, FAST. The reader antenna position in the ML model and the physical model is optimized using GRSM with a goal of achieving good coupling between the tire antennas and the reader antenna. The coupling coefficients for reader antenna position predicted by ML routine is much higher than that of regular routine demonstrating the efficiency of ML. In summary, this work shows that the machine learning based optimization is highly efficient in terms of resource consumption (6 times faster than traditional optimization) and can be applied for solving challenging electromagnetics optimization problems.

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