EMC simulations using source reconstruction

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Introduction

Electromagnetic compatibility (EMC) means that electric components and devices do not interfere with each other or are affected by the environment in unwanted ways. For a given device, such as a mobile phone, television set, microwave oven, antenna, etc., it means making sure on one hand that it does not generate electromagnetic fields that can disturb other devices and on the other hand that it in itself is not overly susceptible to EM conditions that can be expected in its operating environment.

EMC is becoming an increasingly important issue in the automotive industry. Many systems in a car that have in the past been hydraulic or mechanical are being replaced by electromechanical designs, such as drivetrains, power windows, steering, parking brakes, etc. Furthermore, electrically controlled features are being added such as touchscreens, tire pressure monitors, remote keys, wireless charging and various equipment related to autonomous driving. The parts in a car must fulfill various EMC regulations regarding both their impact on other systems and their immunity to being disturbed themselves.

Simulating EMC means including the parts to be studied in a model and determining such quantities as magnetic field, electric field, induced currents, etc., depending on the requirement to be investigated. A common challenge for automotive EMC simulations is that many parts are acquired from suppliers who for IP reasons may not share such data as 3D CAD models, material properties, or excitations. This raises the question of how to perform EMC simulations in the absence of such information. The topic of this paper is to investigate source reconstruction [1] as a possible solution. The main idea is that a proprietary part acting as possible source of EMC failures has a black box representation based on measurements while the remainder of the system is modelled in a conventional manner.

EMC concepts

A common concept in EMC is the source – path – victim model. Source is whatever generates the electromagnetic disturbance and can be for instance electric motors, power converters, antenna transmitters, etc. Victim is the potential target of the source and can among many other things be a sensor, antenna receiver, loudspeaker or electronic circuit board. The path describes how the disturbance from the source is transferred to the victim. Different path types exist corresponding to different subsets of Maxwell's equations:

- Conductive: The EM disturbance is transmitted as currents through conducting objects such as wires, metallic structures or ground.
- Inductive: Magnetic fields are transmitted through air by induction.
- Capacitive: Electric fields are capacitively transmitted through air.
- Radiated: Electromagnetic waves are transmitted through air. This can only occur at reasonably high frequencies.

With regards to simulation in COMSOL, the four coupling path types correspond to the physics interfaces Electric Currents, Magnetic Fields, Electrostatics and Electromagnetic Waves respectively. In this work we shall focus on the inductive path type in which case magnetic fields are of interest and the displacement current term in Ampere's law is neglected. This is valid if the electromagnetic wavelength is much larger than the system to be studied. For instance a source frequency of 100 kHz corresponds to an electromagnetic wavelength of 3000 m which means the assumption is valid for systems with a size of up to at least 30 m.

Source reconstruction

FE simulations typically employ a CAD geometry, material properties and excitations throughout the simulation region. However as mentioned previously, part suppliers will sometimes not share such information. However they may often instead be able to provide a point cloud of magnetic field values, resulting from either measurements or their own FE simulations. This suggests the possibility of generating a black box model from such a point cloud. A conceptually straightforward method of employing the data would be to simply apply those field values as a boundary condition, however this has two drawbacks. One is that it does not take into account the fact that when other parts are placed nearby, they will in general alter the magnetic field surrounding the part and so the applied boundary condition will not be correct. Another is that in order to utilize such a boundary condition, the points need to be reasonably densely distributed over a well defined surface entirely surrounding the part.

A different method will therefore be explored, sometimes used in medical applications and for different purposes, known as source reconstruction. The starting point is the fact that any magnetic field source, however complex, can be approximated arbitrarily well by a set of magnetic point dipoles. For instance a flat coil can be approximated by a number of dipoles distributed in the volume spanned by the coil and its interior and with a total magnetic moment equaling the coil area multiplied by the current. Similarly, the fields generated by induced eddy currents, permanent magnets, and polarized soft magnets can also be represented by magnetic dipoles. Thus, given a point cloud of field values surrounding a part, we seek a distribution of magnetic dipoles that reproduces the magnetic field point cloud within some margin of error. Thereafter, a simulation model can be built in COMSOL that combines this set of dipoles with conventional CAD representations of other relevant parts.

Suppose a point cloud is available in locations $\mathbf{p}_j$, $j=1,2,\ldots,M$ with corresponding field values $\mathbf{B}_{\mathrm{m}}(\mathbf{p}_j)$. Then consider a dipole in position $\mathbf{r}$ with magnetic moment $\mathbf{m}$ and assume no other objects affecting the magnetic field are present. The field $\mathbf{B}_{\mathrm{dp}}$ the dipole generates in point $\mathbf{p}_j$ is

$$\mathbf{B}_{\mathrm{dp}}(\mathbf{p}_j) = \frac{\mu_0}{4\pi|\Delta\mathbf{r}_j|^5}\left(3\Delta\mathbf{r}_j(\mathbf{m}\cdot\Delta\mathbf{r}_j) - |\Delta\mathbf{r}_j|^2\mathbf{m}\right) \quad (1)$$

where $\Delta\mathbf{r}_j = \mathbf{p}_j - \mathbf{r}$. The field from multiple dipoles numbered $i=1,2,\ldots,N$, is the superposition of the fields from individual dipoles i.e.

$$\mathbf{B}_{\mathrm{dp}}(\mathbf{p}_j) = \frac{\mu_0}{4\pi|\Delta\mathbf{r}_{i,j}|^5}\times$$
$$\times\sum_i\left(3\Delta\mathbf{r}_{i,j}(\mathbf{m}_i\cdot\Delta\mathbf{r}_{i,j}) - |\Delta\mathbf{r}_{i,j}|^2\mathbf{m}_i\right) \quad (2)$$

where $\Delta\mathbf{r}_{i,j} = \mathbf{p}_j - \mathbf{r}_i$ and $\mathbf{r}_i$, $\mathbf{m}_i$ are position and magnetic moment of dipole i. The goal is then to find a set of dipole locations and moments $\{\mathbf{r}_i, \mathbf{m}_i\}$ such that the field $\mathbf{B}_{\mathrm{dp}}$ calculated from (2) well approximates the point cloud field $\mathbf{B}_{\mathrm{m}}$ in the points $\mathbf{p}_j$, The optimization procedure is discussed in a later section.

Example application: Wireless charger

In a typical use case, a part supplier would provide a point cloud. This would then provide the basis for an optimization giving a distribution of dipoles. Then a COMSOL simulation model would be set up including the dipoles along with CAD models of other parts that are potential victims. The results could optionally be verified by comparing COMSOL results to measurements.

For IP reasons, we will avoid presenting results for real physical devices and instead focus on investigating the general methodology. Thus instead of using a point cloud received from a part supplier, we implement a traditional 3D model of a fictional part in COMSOL, something that would ordinarily not be available. The model will have two purposes: First it will be used generate the point cloud that would otherwise be provided by a supplier, second it will be combined with victim parts to allow comparisons to the dipole representation and estimate the accuracy of the method.

A wireless charger for electric vehicles is used as example of source part. It contains a transmitter side located in a charging station in the ground and a receiver side residing in a car. Both the transmitter and receiver contain a cylindrical coil, a round ferrite plate for increasing the mutual inductance, and a square aluminum plate for reducing stray magnetic flux, see Fig 1. The car battery can be charged when the car is parked with the receiver positioned right above the transmitter within some tolerance and they together comprise a transformer. A sinusoidal current is applied to the transmitter coil with an industry standard frequency of 85 kHz.

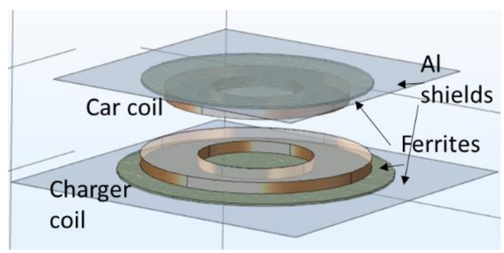

Figure 1. Wireless charger.

All the parts in both the transmitter and receiver will be represented with a single black box multiple dipole model.

Optimization

For the case considered here, only the dipole moments $\mathbf{m}_i$ are used as design variables and the dipole positions $\mathbf{r}_i$ are kept fixed. The objective function is defined by

$$\varepsilon = \|\mathbf{B}_{\mathrm{dp}} - \mathbf{B}_{\mathrm{m}}\|_2^2$$

which is quadratic with respect to the design parameters. This means that the optimization problem is convex and hence a gradient-based optimization algorithm will be efficient since only one local minimum exists, which is also the global minimum. Here, we used the BFGS in the Python SciPy package.

It should be noted that the problem we are trying to solve is an inverse problem [2], i.e. we are trying to determine the source of a measured magnetic field. These types of problems are typically ill-posed due, in most cases, to the fact that there does not exist a unique solution to the problem. In this case, we obtain a reasonable solution by choosing the number of dipoles manually, but for a more general treatment, a method such as Tikhonov regularization or LASSO (Least Absolute Shrinkage and Selection Operator) [3] could be applied.

To investigate the risk of overfitting, we performed simulation experiments, where the sampled magnetic field values were divided into two sets: one training set and one test set. The training set consisted of one layer of points close to the source and the test set consisted of two layers of points farther away from the source. In general, the more parameters you have in the model, e.g. number of dipoles, the higher variance you get in your model (overfitting). If, on the other hand, the number of parameters is too small, the resulting model will have a high bias (underfitting). The bias-variance tradeoff can be handled algorithmically with methods such as LASSO and ridge regression, but here we conducted a manual investigation of the impact of the number of dipoles in the source-reconstruction model.

We investigated different numbers of dipoles in the x, y, and z directions according to $N_x = N_y = N_{xy} = 2, \dots, 10$ and $N_z = 1, \dots, 3$ which resulted in 27 different models with the number of dipoles, $N_{xy}^2 N_z$ ranging from 4 to 300. For easier comparison, the objective function value was normalized to the case $N_z = 1, N_{xy} = 2$ for the training and test data respectively. Fig. 2 shows the optimized objective function value as a function of N_{xy} for the three different values of N_z. As expected, the more parameters we include in the model, the better the fit is to the training data. If we on the other hand evaluate the model on the test data, shown in Fig. 3, we see that there is a clear tendency of overfitting for the models with more dipoles. In this case, the models with $N_z = 1,2$ seem to perform well on the test data up to $N_{xy} = 9$ and the models with $N_z = 3$ seem to perform well up to $N_{xy} = 7$.

If we look at the model performance on the test data as a function of number of dipoles (Fig. 4), we see that, for this case, increasing N_z gives a model with better predictive power when keeping the total number of dipoles fixed.

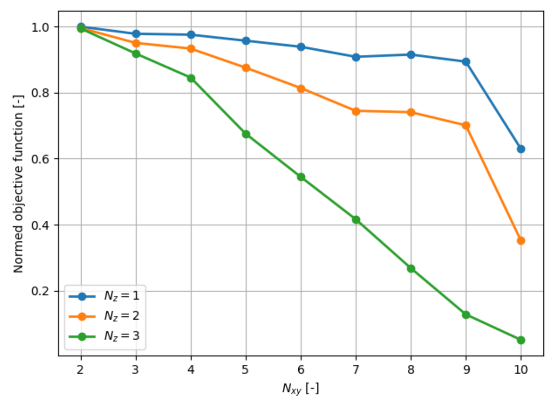

Figure 2. Objective function vs N_{xy} for different N_z for the training data.

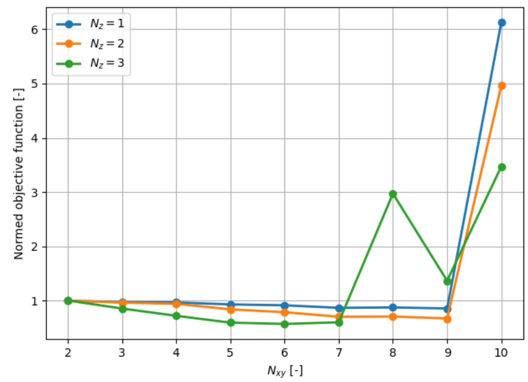

Figure 3. Objective function vs N_{xy} for different N_z for the test data.

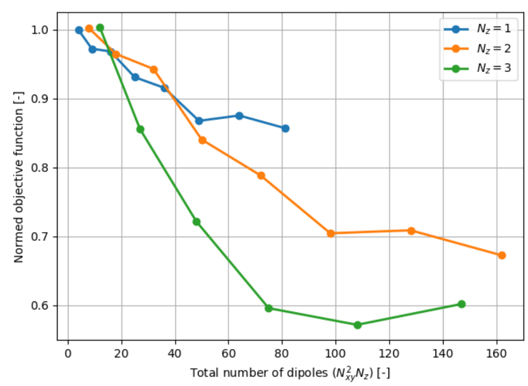

Figure 4. Objective function vs number of dipoles for the test data. In this figure, the optimization results that show clear overfitting according to Fig. 3 have been removed.

Simulation procedure

Ignoring the displacement current term in Maxwell's equations and disregarding electric flux density, the remaining subset of equations to be solved is

$$
\begin{aligned}
\nabla \times \mathbf{H} &= \mathbf{J} \\
\nabla \times \mathbf{E} &= -\,\partial_t \mathbf{B} \qquad (5) \\
\nabla \cdot \mathbf{B} &= 0
\end{aligned}
$$

along with constitutive laws which in the simplest linear case can be written

$$
\begin{aligned}
\mathbf{B} &= \mu \mathbf{H} \qquad (6) \\
\mathbf{J} &= \sigma \mathbf{E}
\end{aligned}
$$

with the usual notations **H** = magnetic field, **B** = magnetic flux density, **E** = electric field, **J** = current density, μ= permeability, σ= conductivity.

The following steps were performed:

1. A 3D model of the wireless charger was implemented in COMSOL with no other sources or objects in the vicinity. **B** field values were evaluated on a 3D grid and exported to a file. These values represent data that would otherwise typically come from a supplier.

2. The results from 1. were used to perform optimization implemented in an external Python script according to the previously described procedure. A grid of 5×5×2 dipoles was eventually used. The resulting dipole values and coordinate positions were written to files.

3. A COMSOL model was set up containing a wire loop inside a metallic box, representing a "victim" component. The dipole coordinate positions and values from step 2 were imported.

4. Another COMSOL model was set up containing a full CAD representation of the wireless charger and the victim.

5. Results from the models in steps 3 and 4 were compared.

The models used in steps 3 and 4 are shown in Fig. 5. All simulations were done in the frequency domain with the Magnetic Field interface. Thin metallic objects often appear in EMC applications and were here present in the aluminum sheets in the charger and the steel box in the victim. Representing them as thin 3D volumes would pose a major modelling challenge since a volumetric mesh would have to feature several layers of elements through the sheet thickness to capture the skin effect. Much more convenient is to model them as surface objects using "Transition Boundary Condition" with the thickness given as a parameter and the skin effect automatically calculated analytically. The dipole definitions were included in the model by employing geometry points for defining the locations and a magnetic dipole source with interpolation tables defining magnetic moments.

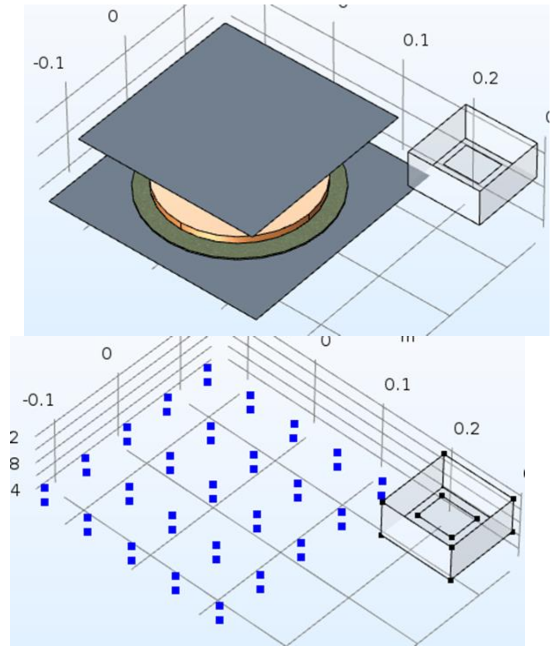

Figure 5. Top: Full model with 3D CAD representation of wireless charger and a victim component. Bottom: Dipole representation of charger using 5x5x2 dipoles along with victim component.

Results

Results are shown in Figs 6-7 comparing results from the full model and the dipole representation. In all cases, **B** is plotted with a common logarithmic scale for the colors, displaying strong similarity in magnitude and direction. The voltage induced in the loop wire in the victim was evaluated to be 4.5mV for the dipole representation and 4.2mV for the full 3D CAD model, giving a difference of 7%.

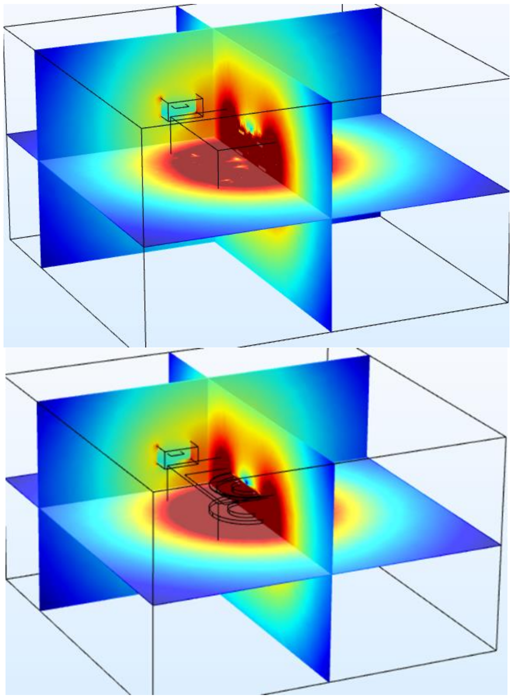

Figure 6. Magnetic field contour plots for dipole representation (top) and full CAD model (bottom).

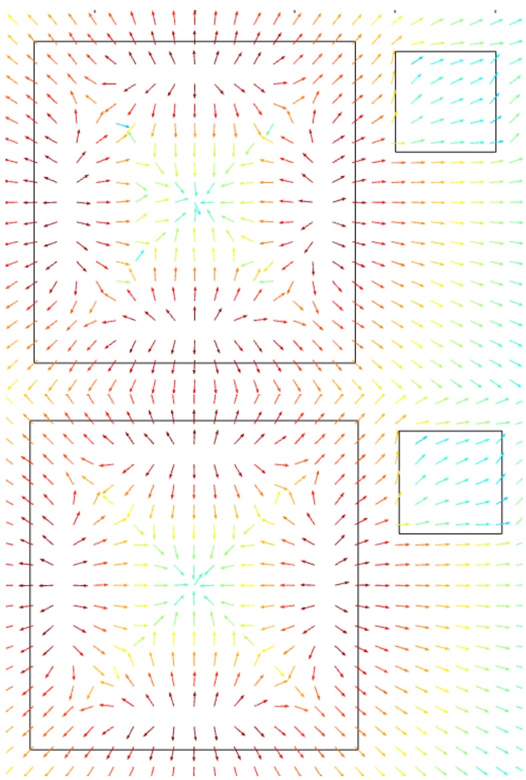

Figure 7. Magnetic field arrow plots for dipole representation (top) and full CAD model (bottom). The victim part is the smaller square in the top right corner.

Conclusions and future work

An initial study has been performed to investigate a possible solution for absence of detailed part models in EMC simulations. A set of magnetic dipoles is matched to a point cloud derived from either measurements or proprietary simulation models. Results are promising and suggest that source reconstruction is a viable approach. Further work should be performed in several areas, including looking at other types of devices, more systematic and refined optimization, considering higher frequencies with wave propagation present, and studying how reliability is affected by noisy input data.

References

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