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Integrating Statistics and Manufacturing Data into Simulation of Permanent Magnet Motor Drives

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Simulating motor drives using Spice, Simulink or other tools is a great way to verify a concept or basic system performance. And through the use of Monte Carlo (MC) and worst-case analysis (WCA), a reasonable estimate of the performance probability distribution can be made. However, MC and WCA techniques are based on assumptions of a normal probability distribution and linear correlations between various system parameters. These techniques are not sufficient in predicting realistic system performance.

In this paper, we propose techniques to modify MC and WCA through the integration of manufacturing data to explain and predict abnormal correlations between various system parameters. These correlations often occur in the prototype or manufacturing phase of a product development cycle and can often go unnoticed until a production ramp up takes place. These techniques are tested and verified on a permanent magnet brushless motor drive system.

Short time to market and exceptional product performance define a company's competitiveness. The complexity of electromagnetic and power electronics products have increased greatly in the last decade. Components, methods and processes are known to develop abnormal and unpredictable correlations during the prototype or manufacturing phase, greatly jeopardizing time to market [1]. It is commonly assumed that the performance of a product follows a normal probability distribution as shown in Fig. 1.

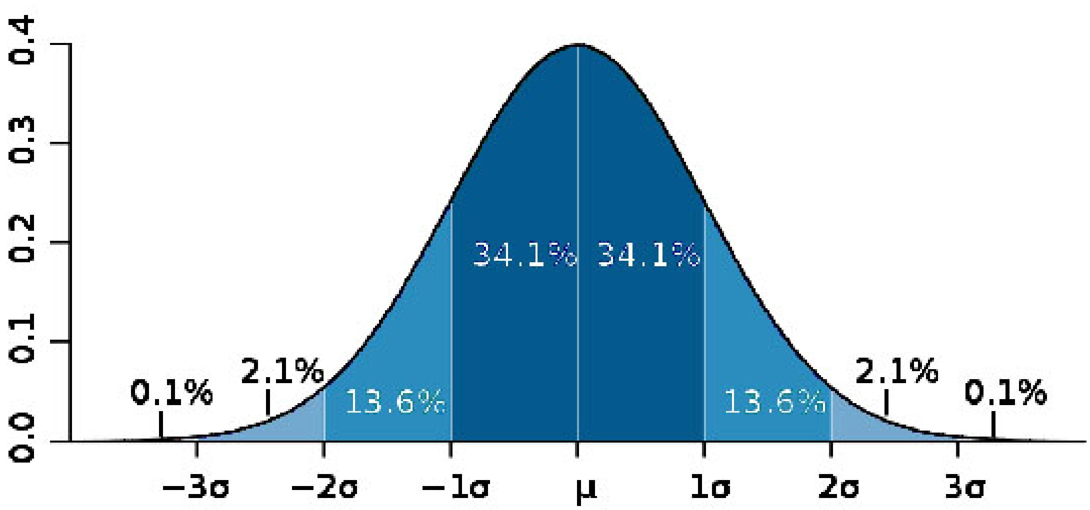

Fig. 1. A normal probability distribution is often assumed for components, methods and processes for MC and WCA.

However as product complexity increases, assumptions of a normal distribution can quickly become invalid during a new product launch. That's because several new and unknown variables are introduced at once during the transition from prototype build to manufacturing ramp up. In this paper, we propose a novel simulation technique that addresses the abnormal correlations between several parameters of a permanent magnet motor drive. Our proposed new simulation technique incorporates MC and WCA in addition to real manufacturing data to identify and predict possible abnormal correlations that cannot be explained through physical equations or laws of physics.

Simulation Using PSpice

Fig. 2 shows a portion of the system diagram for a permanent magnet brushless motor drive system in PSpice. The setup consists of analog behavioral models as well as electrical components. We can run MC and WCA to get a fairly good idea of the system performance based on selected electrical components and devised algorithms. Further integration into an FEA solver could model some of the electromagnetic parameters as well.

A few of the mechanical parameters may be difficult to incorporate into the overall simulation scheme with the given tools without some serious effort. Some of those parameters could be fit related to non-electromagnetic components such as motor housing, bearing etc. Nevertheless, all of those parameters need to be taken into consideration prior to the start of manufacturing in order to predict system performance precisely.

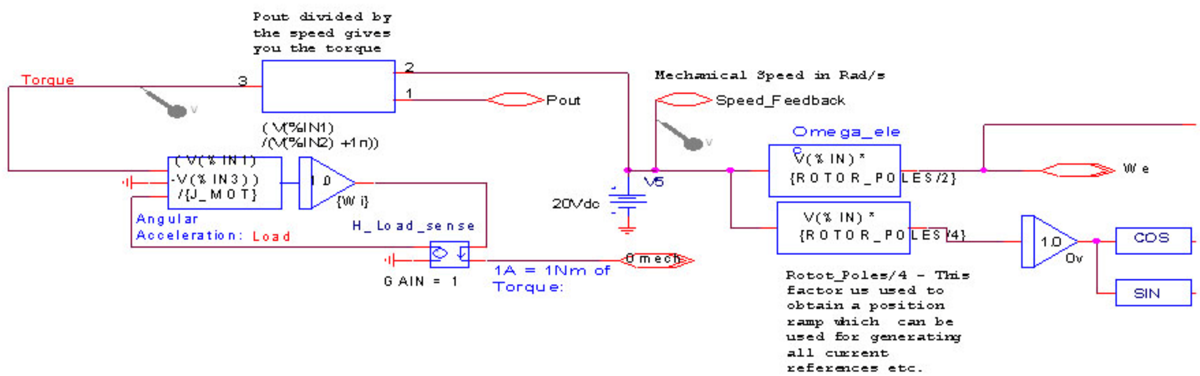

Fig. 2. Permanent magnet brushless motor drive system in PSpice.

The Normal Distribution And Underlying Design Assumptions

A normal distribution is characterized by two parameters: the mean μ and the standard deviation σ as shown in Fig. 1. The mean is a measure of location or center and the standard deviation is a measure of scale or spread. The mean can be any value between ±∞ and the standard deviation must be positive. Each possible value of μ and σ define a specific normal distribution and collectively all possible normal distributions define the normal family. The following underlying assumptions are usually part of the design process.

- All electrical and electronic component values are normally distributed as per Fig. 1.
- All mechanical dimensions are normally distributed within their defined tolerance limits.
- All electrical correlations are created through known physical equations or design constraints or laws of physics.

With the above assumptions, and using the techniques of MC and WCA, we can reliably predict a system's performance. However, the underlying assumptions can change during manufacturing. Probability distributions can shift dramatically towards the right or left extreme and unpredictable correlations can develop. In that case, we are forced to redefine our simulation methods to predict system performance during production ramp up.

Cp and Cpk values help define the deviation of a process or performance from 'normal'. Cp is normally defined as process capacity, a simple and straightforward indicator of process capability and Cpk is process capacity index. In other words, Cp is an index or a number that indicates how closely a process is running to its specification limits, assuming natural and random variation of the process. Generally, a Cpk value of 1.33 or higher is required to satisfy most customers.

Cpk measures how close one is to the target and how consistent one is around the average performance. A process may be performing with minimum variations, but it can be away from the target towards one of the specification limits, which will indicate lower Cpk, and higher Cp. On the other hand, a process may be on average exactly at the target, but the variation in performance could be high (but still lower than the tolerance band i.e. specification interval). In such a case, Cpk will also be lower, but Cp will be high. Cpk will be higher only when one is meeting the target consistently with minimum variation.

The formulas used for calculating Cp and Cpk are:

$$C_p = \frac{UL - LL}{6\sigma} \quad (1)$$

$$C_{pk} = \min of \left[\frac{x - LL}{3\sigma}, \frac{UL - x}{3\sigma} \right] \quad (2)$$

where UL is the upper specification limit, LL is the lower specification limit and x is the actual measurement. It is important to note that the Cp and Cpk concepts can be applied to any electrical, physical or mechanical parameter to gauge its degree of closeness to a normal probability distribution. Our simulation technique incorporates real-time measurements of Cp and Cpk to explore possible correlations between exogenous variables (explained later).

Monte Carlo Analysis (MC)

In this section, we briefly discuss the MC technique and how it is incorporated into our novel simulation method. MC is used to understand the impact of risk and uncertainty in forecasting system performance. Fig. 3 shows how the actual system performance varies from the MC estimation. It is based on estimates of the probability distribution of components, methods and process performance. A forecasting model can be developed using assumptions outlined above. A brief example of a forecasting model is shown in Table 1 where √ indicates the possibility of abnormal relationships.

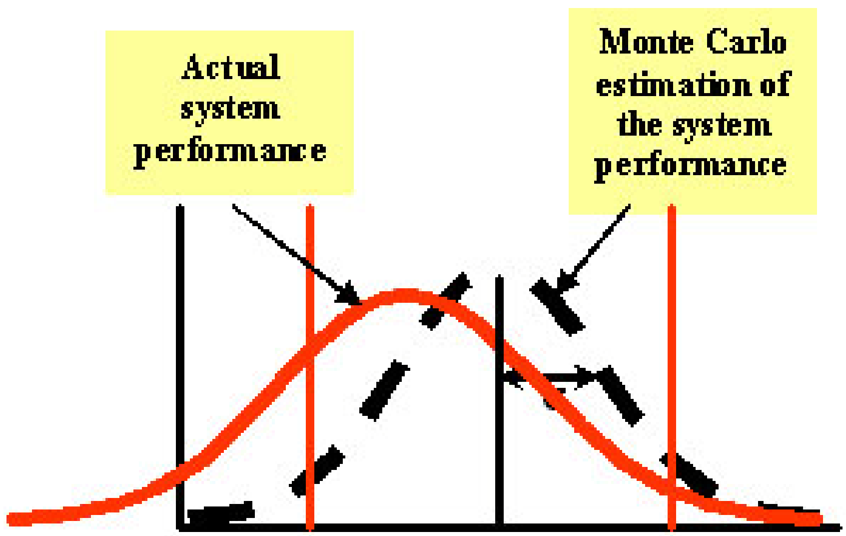

Fig. 3. Monte Carlo estimation of the system versus actual system performance.

Table 1. Forecasting model.

	R_a	R_b	R_c	B	A_g
R_a		√	√	√	√
R_b	√		√	√	√
R_c	√	√		√	√
B	√	√	√		√
A_g	√	√	√	√	

We can always assume a certain probability distribution for the values of parameters such as resistance of coils A, B and C (R_a, R_b, R_c), hall sensor timings, flux density (B), core saturation etc. By using these estimates of probability distributions, we can build a probability distribution for the whole system. If our assumptions are correct we can have a fairly good idea of the system performance during mass production. However in complex electromagnetic and power electronic systems such as a permanent magnet brushless motor drive, such assumptions are often not true and possible abnormal correlations can crop up during manufacturing.

Worst-Case Analysis (WCA)

This is an important technique to study the impact of tolerance limits of all the electronic, electrical and mechanical components. In our paper we demonstrate that WCA only establishes the extreme limits of system behavior. WCA is not capable of predicting shift in normal distribution caused during manufacturing. WCA assumes linear and predictable correlations between variables. Nevertheless, this technique is important to establish correct probability-distribution characteristics.

Fig. 4. shows an example of WCA using a permanent magnet motor. The air gap of this motor is impacted by a number of mechanical components such as housing height, back iron height, magnet height, lamination diameter etc as shown in Fig 5.

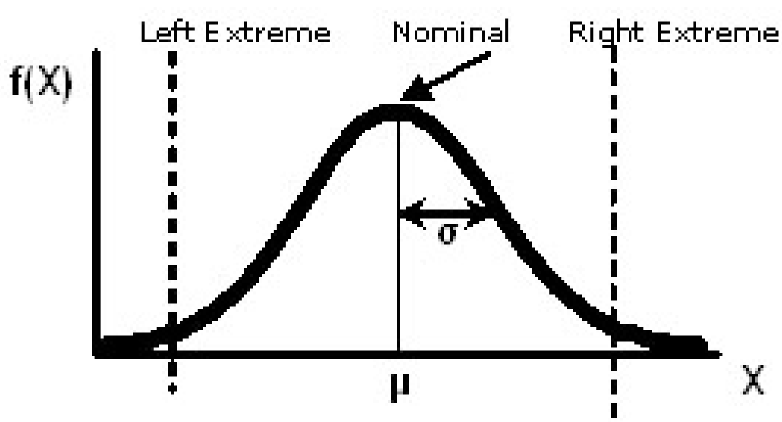

Fig. 4. A WCA example using an outer rotor PM motor. Shown here is the probability distribution of the motor's air gap.

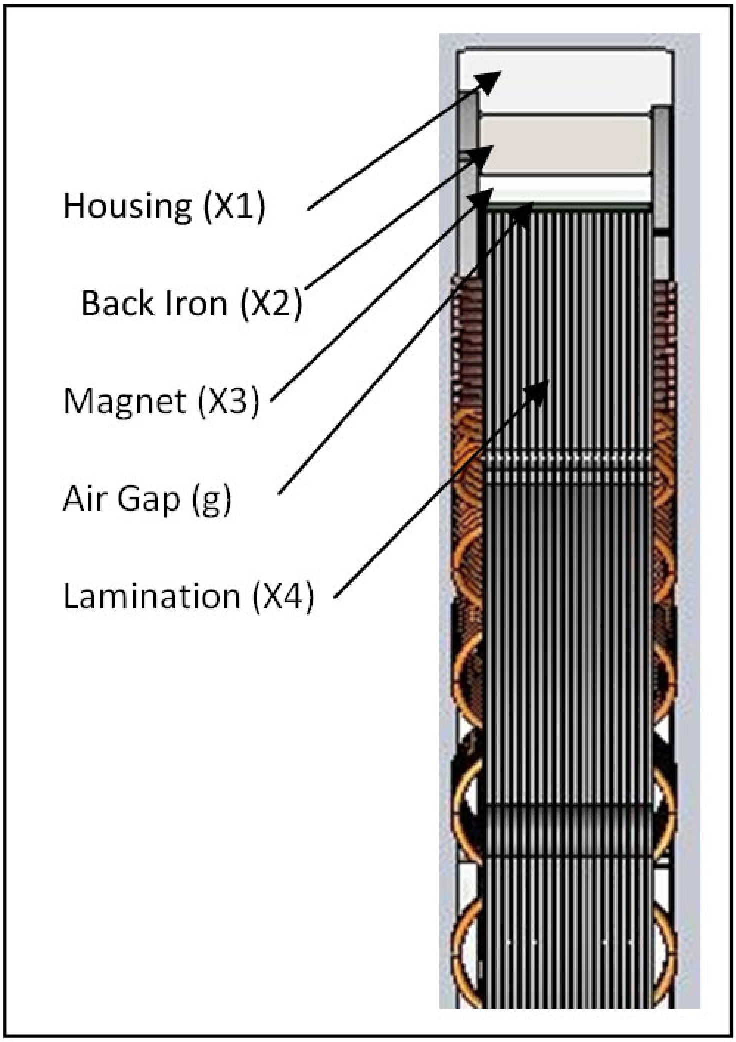

Fig. 5. Cross-sectional area of a PM motor.

A normal distribution is assumed for each of these variables and each of these variables are assumed to be exogenous. Therefore, the air gap value can be assumed to have a normal distribution as shown in Fig. 4. However, if we assume a possible abnormal correlation between X1 and X2 as shown in Fig 6, the probability distribution of the air gap is no longer normal.

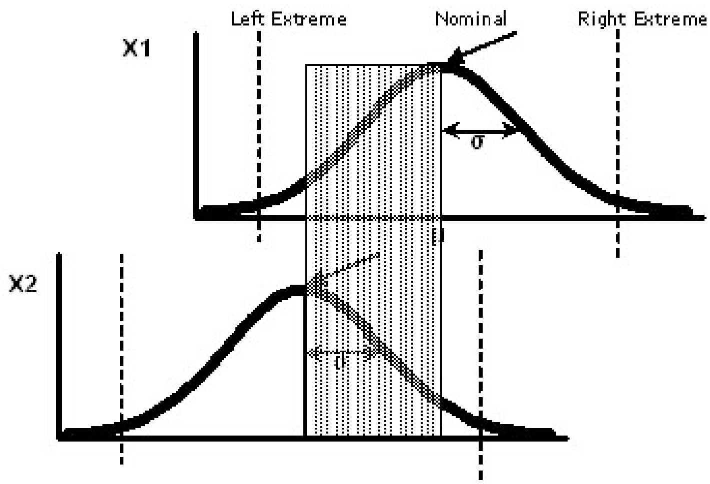

Fig. 6. An example of an abnormal correlation between X1 and X2.

Exogenous And Endogenous Variables

Exogenous variables are the independent variables that affect a model without being affected by it. Its qualitative characteristics and method of generation are not specified. Endogenous variables are the dependent variables generated within a model, therefore a variable whose value is changed by one of the functional relationships in the model. It is important to distinguish between the exogenous and endogenous variables of a system in order to understand the possibility of abnormal correlations as these correlations can only exist among the exogenous variables. Table 2 shows an estimation of a motor's air gap tolerance limits using WCA.

Table 2. WCA involving motor air gap and exogenous variables X1, X2, X3, and X4.

	Variables	**Max.**	**Min.**	**Nom.**
X1	Housing thickness (mm)	7.52	7.48	7.5
X2	Back iron thickness (mm)	7.15	6.85	7.0
X3	Magnet thickness (mm)	3.6	3.4	3.5
X4	Lamination radius (mm)	88.5	88.45	88.5
g	**Air gap (mm)**	**1.3**	**0.73**	**1**

Proposed Simulation Technique

The proposed simulation technique is shown in Fig 7.

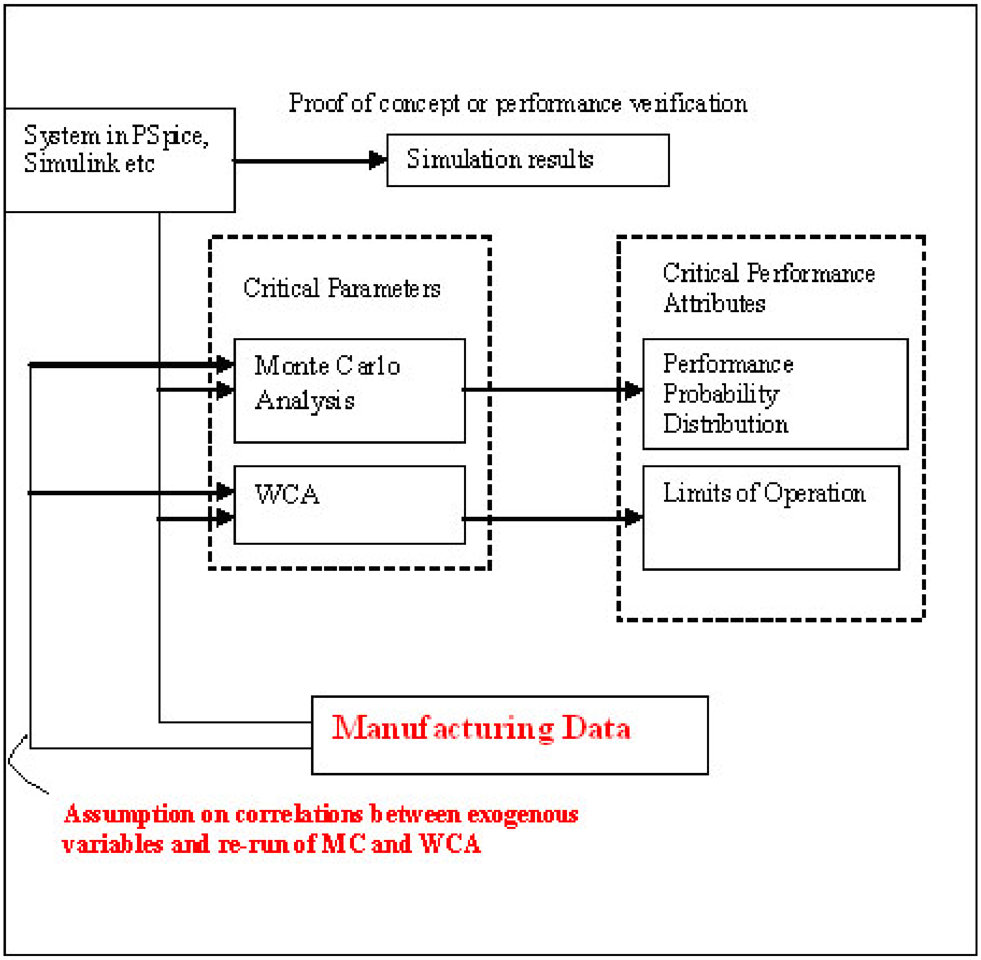

Fig. 7. The proposed simulation technique for permanent magnet motor drives combines Monte Carlo and worst-case analysis with real-manufacturing data to identify and predict possible abnormal correlations that cannot be explained through physical equations or laws of physics.

Essentially, this technique is the usual simulation routine used for proof of concept, MC, WCA, etc. The important difference here is that real-time manufacturing data is fed into the simulation model and the simulation is rerun either to match the real-time system performance or to predict abnormal correlations if system performance is not meeting specifications in spite of successful MC and WCA predictions.

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For further reading on simulation techniques, see the How2Power Design Guide, search the Design Area category and select the Modeling and Simulation subcategory.

