

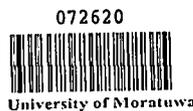
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APPLICATION OF RANDOM FIELD LINEAR MODEL
FOR QUALITY IMPROVEMENT IN
PRODUCT DESIGN

By
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Thesis submitted in fulfilment of the award of Ph.D,
University of Moratuwa, Sri Lanka.



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DECLARATION

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Dedicated to my parents late

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KEY TO ABBREVIATIONS

ANOVA	Analysis of Variance
BLUP	Best Linear Unbiased Predictor
CMR	Composite Mixed Resolution
GAM	Generalized Additive Model
GLM	Generalized Linear Model
IWLS	Iterated Weighted Least Squares
LHS	Latin Hypercube Sampling
LM	Loss Method
LSK	León, Shoemaker and Kacker
MMSE	Maximum Mean Squared Error
MPNLE	Maximum Pseudo Normal Likelihood Estimator
MSE	Mean Squared Error
PerMIA	Performance Measure Independent of Adjustment Factors
PNL	Pseudo Normal Likelihood
RFLM	Random Field Linear Model
RSM	Response Surface Methodology
SN	Signal - Noise
SRS	Simple Random Sample

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ABSTRACT

The quality revolution of the late 80's and 90's led to researches in quality improvement in product and process designs. Taguchi's methodology for quality improvement called robust parameter design gained the interest of practitioners working in industry in quality improvement. Several approaches proposed as alternative to Taguchi's method embraced the important aspects of parameter design and this resulted in a collection of alternatives to Taguchi approach. Some of these alternatives highlighted the use of response surface methodology for quality improvement in engineering designs.

Computer simulation modeling is an important part of engineering design. Running simulators to obtain observations for analysis are very often expensive. Some designs may require several simulator runs to find the appropriate settings of the design parameters. So statistical models are used as surrogates of the computer simulation models for analysis and design optimization. In robust engineering design, the parameter settings of the engineering designs are sought, so that the designed product will be insensitive to the effects of noise factors such as statistical fluctuations in the design parameters or external noise factors such as temperature, humidity that may affect a product's performance.

The modeling approach used in this thesis, models the response from the computer simulation model using the Random Field Linear Model. This model is a multi-dimensional spatial linear model with structure in the covariance



function. The predictor is used for further statistical analysis. The fitting of this model involves the estimation of covariance parameters. The methods of estimation of model parameters and model building are also described. It is also shown that for particular values of the correlation parameters, the model approximates to a multinomial model in the predictor variables.

Latin hypercube sampling design is used for sampling design points for model building and for exploratory data analysis. This design is easy to generate and is found to be useful in multi-level, multi-factor experiments. The LHS designs have better statistical properties for estimation of main effects, interaction effects than simple random sampling designs.

The use of Random Field Linear Model and Latin Hypercube Sampling for modeling and analysis in robust parameter design is illustrated with observations from circuit simulation models. The effect of using prior information on the mean with RFLM is also investigated.