Design of Experiments - A Paradigm Shift from Traditional to Modern Approach

The Statistical Design of Experiments (SDoE) focuses on design and evaluation of any task that intends to portray the experiment by predicting the outcome by introducing a change of the preconditions, which is represented by one or more predictor variables." The change predictor variables are generally hypothesized to result in a change in one respective response variables. Thus many traditional approaches are available in literature to understand the complex relationships among input design parameters and process or product outputs. Nowadays the application of SDoE has wider acceptability and henceforth this session mainly concentrates on a paradigm shift from traditional approaches of SDoE techniques to Modern approaches.

A Study on Neutrosophic Design of Experiments

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Abstract

Real world is full of uncertainties, ambiguities and inaccuracies. It is vital to analyse these phenomena. Neutrosophic logic is the mathematical model to bring clarity to these uncertain, ambiguous, and inaccurate situations. Design of experiments is a systematic technique that permits to study relationship between the input variables and key output variables. It is structured method for collecting facts and making discoveries.

We propose to introduce the neutrosophic design of experiments, which is a generalisation of the classical designs. In this paper, we study the flexible way of handling imprecise elements in design of experiments.

Keywords: Neutrosophic, Design of Experiments

A Statistical Analysis of Factorial Experiments Using Response Surface Methodology

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Abstract

Simple experiments like Randomized Block Designs (RBD) and Latin Square Design (LSD) are only one factor that can be tested at a time. If we want more than one factor tested, we must conduct separate simple experiments for each factors. The factorial experiments are introduced in which more than one factor can be tested simultaneously. Factorial experiments may be classified into two types symmetrical and asymmetrical factorial experiments. The number of level for each factor is the same, and then it is called the symmetrical factorial experiment. Otherwise, asymmetrical factorial experiments. In many problems, it is impossible to perform a complete replicate of a factorial design in one block. Confounding is a design technique for arranging a complete factorial experiment in blocks, where the block size is smaller than the number of treatment combinations in one replicate. The technique causes information about certain treatment effects (usually high-order interactions) to be indistinguishable from or confounded with blocks. They are two types, namely partial and total or complete confounding. In the fractional factorial design, as the no of factors in 2^n or 3^n factorial experiment increases, the total number of treatment combinations in the design is very large. In such a case, it is very difficult to organize because the total number of treatment combinations becomes very large. The demand of resources is so great and hence it may not be also possible for the experimental to provide them. Response Surface Methodology (RSM) was introduced by George E.P. Box and K.B.Wilson in 1951. The RSM is a collection of mathematical and statistical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response. For example, suppose that a chemical engineer wishes to find the levels of temperature (x_1) and pressure (x_2) that maximize the yield (y) of a process. The process yield is a function of the levels of temperature and pressure, say $y = f\left(x_1, x_2\right) + \epsilon$ where ϵ represents the noise or error observed in the response y. If we denote the expected response by $E(y) = f(x_1, x_2) = \eta$, then the surface represented by $\eta = f\left(x_1, x_2\right)$ is called a response surface. If the response is well modeled by a linear function of the independent variables, then the approximating function is the first-order model is $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon$ and the second-order model $y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_i x_j + \epsilon$. Almost all RSM problems use one or both models. In this paper, a statistical analysis of factorial experiments using RSM with numerical examples of medical, agricultural and industrial fields.

Key words: Factorial Experiments, Confounding, RSM.

Dealing with non-response arise due to sensitive issues

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Abstract

In sample surveys, when we need information regarding sensitive issues which people often do not prefer to share with others. In such situations this is also awkward for interviewers to ask the direct questions related to confidential and private matters of interviewees. An approach towards the open queries about sensitive issues generally results in the high non-response rates or misleading answers. To avoid the situation of non-response or misleading response during surveys due to sensitive nature of characteristic, the randomized response technique is the most applicable tool to reduce social desirability bias and is widely used in survey interviews.

Keywords: Non-response, Sensitive issues, Randomized response technique.

Advanced Statistical Approach in Hydrology with Special Reference to Impact of Climate Change on Water Resources Management

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The Climate change is one of the most severe challenges in the recent century. climate change effecting the different sectors like agriculture, coastal, natural ecosystem, water resources etc across the world. Among those, water resources management is one of the most affected fields due to the strong relationship between climate and water resources. Climate change alters timing and magnitude of precipitation, evapotranspiration, runoff and soil moisture. Such changes have significant consequences on water resources planning and management. Statistical and machine learning modelling approaches are one of the best ways to analysis the changes and to envisage the future impact on water resources. Advanced trend analysis techniques like Modified Mann-Kendall Test, Innovative trend analysis and, Innovative Polygonal Trend Analysis (IPTA) are most applicable techniques to study the long-term moment in the precipitation and river discharge studies. The Pettit test, standard normal homogeneity test etc are applicable for Change in point detection analysis. Forecasting models like Autoregressive integrated moving average (ARIMA), Artificial Neural Network (ANN), Support Vector Machine (SVM), Hybrid models are applicable for short term forecasting of water series. The machine learning and standard statistical downscaling techniques like Nural network family models, regression method etc simulate the longer future climate change scenarios by exploring the empirical relationship found between the projected local variable and the predictor variables. Statistical uncertainty analysis is also one of the booming approaches to increase the efficiency of hydrological models like Soil & Water Assessment Tool (SWAT), MIKE etc.

Keywords: Climate Change, Water Resource Management, Time Series Modelling, Machine Learning modelling, Uncertainty Analysis.