Part I

Optimization Method and their application

Optimization with Artificial Intelligence and soft computing (AI and SC) provides a powerful set of tools for solving a complex problem that are intractable using traditional methods. By mimicking natural processes and learning from data, AI and SC techniques have proven effective in various domains including industry, finance, healthcare and energy.

Application of Soft Computing and AI in Industrial Optimization are widely used in manufacturing to optimize production processes, reduce costs and improve product quality. In Financial Optimization, the machine learning plays an important role to optimize stock portfolios by predicting price movements while fuzzy logic can handle the uncertainty in financial decision making. In the healthcare for optimizing treatment plans, drug discovery and hospital resource management. Reinforcement learning can optimize treatment strategies by learning from patient data while genetic algorithm can aid in discovering new drugs. These techniques have ability to handle more complex, uncertain and dynamic optimization problems and we can expand them for future innovation.

The Part-I dedicated to Optimization Techniques and Their applications which consists of Shannon- information entropy maximization, Fuzzy support vector machines, Power supply queuing models in fuzzy environment, A MCDM Approach for Selection of Lean 4.0 tools in Manufacturing Sector, Spider Wasp Optimizer technique for optimization, Reinforcement Learning for profit optimization, Optimization in sustainable Inventory Management, Fractional integral inequalities for strongly -convex functions, Numerical study on fluid flow and heat transfer, Design and analysis of a novel elliptic curve for cryptography applications.

There are some challenges to use AI and soft computing techniques which are computationally expensive and difficult in their results interpretability.

The open area of future research of optimization algorithm through AI is focused on the time complexity in computation.

Information theory-based approach through Shannon-entropy maximization in relation to surface temperature during pre-monsoon season over Northeast India

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Abstract— **Rather than investigating the physical details of the pre-monsoon thunderstorms of northeastern India, a mathematical analysis has been done to determine the relative significance of several important surface parameters, such as surface temperature, relative humidity, and air pressure, in producing severe thunderstorms over the aforementioned region. We have examined the dataset associated with this meteorological event using the Shannon entropy maximization technique. Finally, surface temperature has been found to be the main factor responsible for the formation of pre-monsoon thunderstorms. Relative humidity and air pressure are the least important factors.**

Keywords— Shannon-entropy; thunderstorms; pre-monsoon; surface temperature; northeast India

I. INTRODUCTION

The pre-monsoon thunderstorm, known locally as a Nor'wester, is observed as a mesoscale event. During the premonsoon season, from March to May, a storm of this type moves over northeastern India. Pre-monsoon thunderstorms are usually accompanied with heavy rain, strong gusts, hail, and other phenomena, hence it has proven challenging for atmospheric scientists to produce an accurate forecast with ample warning. Nearly all studies concerning the forecasting of severe storms have been based on statistical or numerical techniques (Murphy et al. 1989, Wilks 1997, Kumar et al. 1996).

The eight states that constitute Northeast India (NEI) are extremely vulnerable to changes in the environment. Using a new complete surface temperature data set for India, temperature changes over seven decades are plotted in order to explore trends and possible effects of global warming. Pre-monsoon, summer monsoon, and post-monsoon are the three categories into which the data set is split in order to examine the temperature patterns during these periods. Over the past few decades, meteorologists have grown concerned about global warming. The multi-decadal trends of surface temperature change over India were examined in a recent study, according to Ross et al. (2018). It was found that although the northeast and southwest regions of India saw cooling, the northwest and southern regions recorded warming. As several studies have shown (Dash et al. 2007, Kothawale et al. 2010, Sonali and Kumar 2013), it is important to measure the ambient temperature at specific periods.

One of the natural occurrences that can happen anywhere in the world at any time is a thunderstorm, which is caused by intense convective activity. This type of meteorological phenomena, also referred to as a hailstorm or lightning storm, is characterised by powerful winds, lightning, torrential rain, and occasionally hail or snow. Despite being a transient phenomenon, there is a significant chance that it will cause grave harm to both human life and property. Thunderstorms are more common in many areas of the Indian subcontinent during the pre-monsoon months of March through May.

Operational weather forecasters worldwide have acknowledged that forecast uncertainties are caused by inaccuracies in the numerical weather prediction models and uncertainty related to the initial conditions used to initialise the models. The research has also highlighted the possibility that a probabilistic prediction, which contains more information than a deterministic forecast, could help the forecasts (Palmer 2000; Richardson 2000). The concept of entropy of a random variable was first developed by Rudolf Clausius in 1850, and Ludwig Boltzmann gave it a statistical meaning in the 1870s by establishing its connection to statistical mechanics. This marked the beginning of the contemporary era of ergodic theory. Later contributions by J. Willard Gibbs in thermodynamics and Von Neumann in quantum mechanics expanded on the idea of entropy. It was presented into information theory by Claude Shannon in 1948. The development of information theory's coding theorems depends heavily on the long-term behaviour of the random process, which is usefully revealed by the entropy. For an in-depth examination of the Shannon entropy, refer to Grey (1990) and its associated references. Researchers in different fields as well as mathematicians who study information theory have expanded Shannon's fundamental methodology to include ever-more-general models of information sources, coding schemes, and performance metrics. The relative entropy measures both the signal and dispersion parts of the information content from observations, whereas the Shannon entropy difference only measures the dispersion part, according to Xu's (2007) thorough analysis of the differences between the two measures of information content and information loss.

In this work, a Shannon entropy-based method has been used to rank some important surface parameters associated with this kind of thunderstorm. The inputs for this inquiry have been the percentage changes in the magnitudes of the relevant parameters. The entropy-based method has been applied to determine the variation of entropy with respect to the probability distributions corresponding to the expected percentage changes in the parameters under investigation. The parameter with the biggest fluctuation in entropy with change in the expected change in magnitude % has been shown to be the most important one associated with the pre-monsoon thunderstorm in the region. Air pressure, relative humidity, and surface temperature are the three surface parameters that are tested in this work.

II. METHODOLOGY

A. Data and Analysis

65 thunderstorms that occurred over the cities of Kolkata, Bhubaneswar, Agartala, and Gopalpur were investigated in this study. Before and after the thunderstorms, the study measured the values of the previously specified parameters, and it computed the percentage changes in the parameters that were caused by the thunderstorms.

B. Shannon-entropy maximization

We will introduce a methodology in this section that is predicated on the classical principle of probability theory, which is also known as the principle of insufficient reason. According to this concept, any probability distribution that is at odds with the information at hand must be excluded from our approach. The probability distributions that acknowledge our ignorance to the fullest extent are selected from the rest. Maximum entropy results from them (Lesne 2014).

When examining a probability distribution function (PDF), which is represented by a vector f with n components, where the ith component indicates the incidence of the ith outcome, we can write Equation (1) as follows (Roulston and Smith 2002).

$$H(p) = -\sum_{i=1}^{n} p_i \ln p_i \qquad (1)$$

we venture to maximize H(p).

The constraints are:

$$p_i \geq 0 \ \forall i$$

$$\sum_{i=1}^{n} p_i = 1$$

$$E(x) = \sum_{i=1}^{n} p_i \, x_i$$

We construct the Lagrangian,

$$L = -\sum_{i=1}^{n} p_i \ln p_i - \alpha\left(\sum_{i=1}^{n} p_i - 1\right) - \beta\left(\sum_{i=1}^{n} p_i \, x_i - E(x)\right) \qquad (2)$$

where α and β are Lagrange multipliers.

After partially differentiating equation (2), we obtain:

$$\frac{\partial L}{\partial p_i} = -\lambda n p_i - 1 - \alpha - \beta x_i = 0 \qquad (3)$$

$$\frac{\partial L}{\partial \alpha} = 1 - \sum_{i=1}^{n} p_i \qquad (4)$$

$$\frac{\partial L}{\partial \beta} = E(x) - \sum_{i=1}^{n} p_i \, x_i \qquad (5)$$

Using Eq. (3) and i=1,2, 3……..,n

$$\begin{aligned} p_1 &= \exp(-1 - \alpha - \beta x_1) \\ p_2 &= \exp(-1 - \alpha - \beta x_2) \\ &. \\ p_n &= \exp(-1 - \alpha - \beta x_n) \end{aligned} \qquad (6)$$

So, $p_i = \frac{\exp(-\beta x_i)}{\sum_{k=1}^{n} \exp(-\beta x_k)}$ (7)

Therefore,

$$E(x) = \frac{\sum_{i=1}^{n} x_i \exp(-\beta x_i)}{\sum_{i=1}^{n} \exp(-\beta x_i)}$$

$$\Rightarrow \sum_{i=1}^{n} [x_i - E(x)] \exp(-\beta x_i) = 0 \qquad (8)$$

Maximum $H(p)$ is attained when (8) is solved for β and the result is substituted into (7) to yield maximum entropy probabilities.

III. Results,Discussions and Conclusions

In the present study, we have changed n in Equation (8) from 1 to 65 for each parameter. It has been determined that the expected changes (%) in the parameter magnitudes are represented by the E(x). Using the Newton-Raphson approach, the β in Eq. (8) has been determined. Every solution for β has produced a maximum entropy probability distribution. For each equation, the entropies defined in Eq. (1) have been computed using these probability densities. The results have been compiled and are shown in Table 1. It is evident from this table that the surface temperature has had the greatest variation in entropy value, while the air pressure has experienced the least amount of change. Changes in surface temperature are therefore more likely to occur as a result of intense thunderstorms during the pre-monsoon season than changes in relative humidity and air pressure. The strongest contribution from surface temperature (among the three parameters taken into consideration) to the formation of new, intense thunderstorms is thus suggested by the feedback from these parameters.

TABLE I. A TABULAR DISPLAY OF THE ENTROPIES LINKED TO VARIOUS ANTICIPATED CHANGES (%) IN A FEW KEY PARAMETERS AS A RESULT OF THUNDERSTORMS.

Expected change in the magnitude of the parameter due to thunderstorm (%)	**Entropy associated with surface temperature.**	**Entropy associated with relative humidity.**	**Entropy associated with air-pressure.**
5%	13.08	10.76	16.02
6%	11.08	10.32	15.99
7%	10.01	9.57	15.00
8%	9.17	8.99	14.93
9%	7.22	7.88	14.14
10%	5.31	6.93	14.00
11%	3.14	5.99	13.57

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