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New decision support system for strategic planning in process industries: Computational results

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A R T I C L E I N F O

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A B S T R A C T

The impact of a Stochastic Linear Programming (SLP) based Decision Support System in a manufacturing company, such as an integrated aluminum plant, is measured by two important parameters, the VSS and EVPI. With the real data of an integrated steel plant in India, we demonstrate that SLP based DSS can be very effective in managing demand uncertainty and performing futuristic integrated planning, and their financial impact can be in millions of dollars. A two stage stochastic programming model with recourse is implemented in the DSS here. A set of experiments is conducted. Real data from an aluminum company is used to validate the system. The importance of SLP based DSS can be realized from the fact that the value of the stochastic solution (VSS) is USD 3.58 million with 30% demand variability and equally likely demand distribution. The VSS as a percentage of Expectation of Expected Value (EEV) ranges from 0.90% to 18.93% across experiments.

1. Introduction and motivation

One of the major difficulties in the application of important management science techniques is the absence of user friendly, menu-driven tools so that a manager can take a decision without any knowledge of OR/MS. In this background, Geoffrion (1989), in his famous IFORS address came up with the characteristics of a modelling environment and suggested that a modelling environment in the future will be model data independent, model solver independent and will address uncertainties. Stochastic Linear Programming (SLP) is one such tool that has wide applications in management and such a SLP based Decision Support System (DSS) has been designed in Gupta, Dutta, and Fourer (2014), but the application of the SLP model in some process industries was not taken into account in that article. Earlier Dutta (1996) developed an optimization based DSS and showed its application in four different industries. A generic multi-period optimization based DSS was first introduced in Dutta and Fourer (2008). Such proposals indicate the need for SLP in process industries, and the significance of using SLP is discussed here.

The objective of this article is to unveil the importance of SLP in creating an adaptive and convenient DSS for strategic perception. The SLP utilized here for a multi-scenario, multi-period optimization based DSS can be simplified in two stages. Given an uncertainty in the second stage with a given probability distribution, a decision has to be made in the first stage where an objective function needs to be maximized or minimized. The effectiveness of an SLP can be judged by two parameters, the value of stochastic solution and the expected value of perfect information. The gain in Expected Value of Perfect Information (EVPI) and VSS by applying SLP in a process industry like aluminum is reflected here. Although SLP has been in use, there is hardly any study that deals with the variation of EVPI and VSS with the variation of skewness of the distribution, which is addressed in this article. By conducting about 108 experiments on this model with different levels of coefficient of variation of demand, we observe certain trends and answer the following questions:

a. How does the SLP solution change with the change in the discrete probability distribution of demand?
b. How does the (VSS) change with changes in demand variability?
c. How does the expected value of perfect information (EVPI) change with an increase in the demand variability?
d. How does the EVPI change with the change in the discrete probability distribution of demand?
e. How does the VSS change w.r.t. EVPI with the change in the discrete probability distribution of demand and the demand volatility?

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Nomenclature

M	is the set of Materials
F	is the set of Facilities
A	is the set of Activities
T	is the set of Time Periods
S	is the set of Storage Areas
L	is the set of Scenarios
X	indicates the decision variables
DSS	Decision Support Systems
SLP	Stochastic linear Programming
MVS	Mean Value Solution
PIS	Perfect Information Solution
EEV	Expectation of Expected values

This paper makes fundamental contributions in two areas. First it shows that it is possible to develop an user-friendly menu driven, paradigm neutral SLP based DSS for a process industry and derive significant profit and revenue improvement. Second, based on the answers to the above five questions, some patterns in the variations are observed and studied in this article, which we are presenting for the first time.

This article introduces the need for an optimization based DSS, and its historical development process by current researchers in the first section. The comprehensive review of literature on the application of SLP in modeling uncertainty is explored in the second section. Section 3 introduces the two stage stochastic programming with recourse. Section 4 presents the process flow diagram of an integrated aluminum plant. The optimization steps and key features of the DSS are explained in Section 5. In Section 6, issues related to uncertainty, designing the experiments using the demand variations, and defining the key parameters used to measure the performance of SLP models are explained. The application of the two-stage SLP with recourse model and DSS in an aluminum company and in addition to the results of testing the SLP model with the real data and the designed experiments, some key findings observed from the results are presented in Section 7. Section 8 represents the profitable utilization of this model to practitioners in situations of uncertainty. Section 9 suggests the future scope and possible extensions of the research. Since some readers may not be familiar with SLP, terms like Mean Value (MV) Solution, Expectation of Expected Value (EEV) Solution, Perfect Information (PI) solution and Stochastic Linear Programming (SLP) solutions are explained.

2. Literature survey

First, the origin of stochastic programming with recourse refers to Dantzig (1957) who presented SLP as a simple deterministic equivalent linear program. While there are several papers on stochastic programming with recourse, Fragniere and Gondzio (2002) defined the term recourse as different realizations of the states of nature (or random parameters) at each time period. A survey of stochastic programming by Birge (1997) argues that with the application of SLP based models, it is possible to make flexible, "near optimal" and robust decisions that help decision makers in allocating resources when faced with an uncertain future. Second, the application of SLP to different industries is discussed. Drawing motivation from the seminal work of Fourer (1997) in the database structure of a class of mathematical models, studies on LP based DSS in process industries in deterministic environments and the need for SLP are demonstrated.

A collection of recent SLP test problems for 11 different families of contexts are discussed in the literature by Ariyawansa (2004). Another survey of using stochastic programming in the supply chain for modeling demand uncertainty in ALM problems is presented by Sodhi and Tang (2009). The study also presented an instance of a stochastic programming model to manage the risk pertaining to unmet demand in discrete production and supply chain planning. An ALM model for open pension schemes based on multistage stochastic programing with a detailed demonstration of a risk-based regulation was proposed by Duarte, Valladão and Veiga (2017). In contrast to the earlier mentioned studies, our research in this paper presents the application of stochastic programming in the continuous production of finished aluminum. Motivation for the current research came from earlier works of Dutta, Sinha, Roy, and Mitter (1994) and Sinha et al. (1995). Further publications such as Dutta (1996), Dutta and Fourer (2004), and Dutta and Fourer (2008), discussed a multi-period optimization based DSS. The authors demonstrated that this DSS can be used by many process industries like steel, pharmaceuticals and aluminum. The fundamental principles of relational database construction to represent a linear program were described for a single period model by Fourer (1997). In further extension of that work, Dutta and Fourer (2008) discussed the database principles for multi-period environment.

Other than the field of supply chain management, there are publications on modeling uncertainty using SLP in the airline industry, electric power generation, telecommunication network planning, and financial planning including asset liability management (Rao et al., 2014). SLP models have been developed for a variety of fields including air fleet management by Ferguson and Dantzig (1956), electrical power generation by Sherali, Soyster, Murphy, and Sen (1984), reservoir water management, telecommunication network planning by Sen (1994), financial planning by Mulvey (1991) and Mulvey and Vladimirou (1992), multi-period portfolio investment by Chen and Yang (2017). Again Yang, Li, Jiao and Wang (2018) used the stochastic programming approach to manage the uncertainty in product configuration. Huang, Wu and Hsu (2016) developed a multi-region optimization model based on a two-stage stochastic programming framework for the regional-scale electricity planning to incorporate the demand uncertainty. A complete review of the extensive literature on stochastic programming and its applications in general and in the context of process industries in particular is beyond the scope of this paper. Extensive literature on probabilistic modeling and stochastic programming can be referred to in Birge (1997), Raghunathan and Tadikamalla (1992), Frauendorfer (1992) and Marti & Kall (1997).

While looking into the recent applications of new algorithms, we find that Modiri-Delshad, Kaboli, Hr, Taslimi-Renani, and Rahim (2016) have discussed the backtracking algorithms, while Kaboli, Selvaraj, and Rahim (2016) discuss long term electric energy consumption forecasting *via* artificial cooperative search algorithms. The rainfall optimization, a population based algorithm has been discussed by Kaboli, Selvaraj, and Rahim (2017). Another work by Kaboli, Fallahpour, Selvaraj, and Rahim (2017) discusses long term electric energy consumption formulating problems.

A recent application of a stochastic quadratic programming model and a decomposition algorithm to compute an optimal sales policy in dairy farms of Fonterra, New Zealand has been reported by Guan and Philpott (2011). The sales policy developed was later tested using simulation against a deterministic policy. The model captures uncertainty in the milk supply, price-demand curves and contracting. Ding, Yang and Liu (2016) record a substance flow analysis of the aluminum industry in China, which helps to make decisions to enhance the resource efficiency of the Aluminum industry. The focus of the research presented in this paper is on the application of a two stage stochastic programming in an aluminum plant; we looked for reported literature in this area. The SLP application reported by Summerfield and Dror (2013) is in the context of the biform game, where a single firm or a number of firms choose their production capacities as the game's strategy in the first stage, and form coalitions in the second stage to deliver the best value among them. Though the application is of a two