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Analytics with Stochastic Optimization: Experimental Results of Demand Uncertainty in A Process Industry

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Abstract. The key objective of the research is to report the results of testing of a two stage stochastic linear programming (SLP) model with recourse using a multi scenario, multi period, menu driven user friendly DSS in a North American steel company. The SLP model and the DSS is generic which can be applied to any process industry. It is capable of configuring multiple materials, multiple facilities, multiple activities and multiple storage areas. The DSS is developed using 4th Dimension programming language, and the SLP model was solved using the IBM CPLEX solver. The value of the SLP solution derived from the experimentation of the DSS with a real-world instance of one steel mill is 1.61%, which is equivalent to a potential benefit of US\$ 24.61 million.

A set of experiments were designed based on the potential joint probability scenarios, and the demand distributions expected skewness. The research reports a few interesting patterns emerged from optimization results when the volatility in demand of finished steel rises and the distribution of the demand skewness changes from left to right tail. The academic contribution of this research is two folds. Firstly, the depicting potential contribution to profit in a steel company using a SLP based DSS under probabilistic demand scenarios. Secondly, the optimization experiments confirm that the value of SLP solution increases with the increase in demand uncertainty. The research has applied implications that the practicing managers would be encouraged to look for more optimization based business solutions, and the prescriptive analytics discipline will fetch more scholarly and industry attention.

Keywords: Decision support system, planning with optimization, stochastic programming,

1 INTRODUCTION AND MOTIVATION

In the field of decision support systems (DSS), analytics and digitization are the two new concepts. Stochastic Linear Programming (SLP) is one tool that synthesizes mathematical programming, Decision theory, and statistics. SLP is an important tool in managing an uncertain business environment and making an optimal managerial decision. In the two stage SLP with recourse there are two stages of decision making. The decisions of the first stage are taken before the realization of the outcomes from random parameters. The second stage is a rectification process where the parameters' randomness is considered with an objective function where long-term expected profits can be maximized.

The stochastic linear programming is a very important area of research from present businesses point of view. The industry 4.0 has taken place. Many new technologies are emerging to address the business environment uncertainties. The SLP is one of the prescriptive analytics modeling tool to address this uncertainty in the demand and the other critical parameters of the optimization models. Presently the corporate managers do the planning based on intuition, and the scientific methods of optimization planning have started to take place in a few founding industries such as airlines, hotels, and FMCG. A few manufacturing firms have also made attempts in this area by purchasing user friendly software produced by IBM, and other market leaders. The attempts have been made to integrate such planning and optimization software with the existing ERP systems of the organizations. These attempts have not been much successful so far. The scale of benefits from optimization are now very much known to the practicing managers and greatly appreciated. The INFORMS prestigious Franz Edelman award is given every year to the organizations practice and demonstrate the realization of the profits from large scale optimization implementation in their industries.

A series of earlier publications, namely [1–5] which deals with DSS in process industry using multi-period optimization is the motivation behind this present research. A study [6] described a customized DSS for a North-American integrated steel plant that helped achieve a 16% to 17% increment in its bottom line. Similarly, the DSS resulted in an impact of 6.72% and 12.46% when real-world data from an integrated aluminum and a pharmaceutical firm, respectively, were used. This study is motivated by this high impact potential.

The results of the applications in process industries were discussed using SLP's key performance parameters like Value of Stochastic Solution (VSS), Expectation of Expected Solution (EEV), Expected Value of Perfect Information (EVPI). We depict the practice implications of modeling under probabilistic scenarios. The research is an initiative to model production operations with probabilistic demand of finished steel using an SLP approach. It further demonstrates how managers of companies with little knowledge of OR/MS can impact their profitability using a generic and user-friendly SLP-based DSS [6].

The SLP based DSS is capable of addressing the following questions:

1. How does the VSS vary with demand variability?
2. How does modifying demand variability impact the EVPI?
3. How does the probability distribution of demand impact the VSS?

4. How does the discrete empirical probability distribution of demand impact the EVPI?

The rest of the paper is organized as review of literature in section 2, the optimization model in section 3, the design of database and model definition in section 4, and DSS application in in section 5 with section 6 as results and conclusion.

2 REVIEW OF RELATED LITERATURE

This work was also motivated by [2] on mathematical modeling for integrated steel plant. A linear program was presented [1] by describing the fundamental principles of relational database construction. The modeling evidences are a North American steel mill [2] to a Western Indian pharma firm [3] and an Eastern Indian aluminium company [7].

An SLP survey [8] argues that flexible and robust "near-optimal" resource allocation decisions can be made with SLP models in the face of uncertainty. Earlier studies [2, 4] developed design principles of a multi-period linear programming model and evaluated the optimization-based DSS with a real data set. Literature [3, 7] confirmed a potential substantial impact in financial terms with a DSS in a pharmaceutical company and an aluminum plant. It is observed that other than [3, 9] little has been documented in the literature on 2 stage SLP-based DSS in a process industry.

Reported studies [4, 6, 7] discussed the basic concepts of database structure and SLP-based DSS design. We reviewed the relevant literature and presented in the context of our research in Table 1.

Table 1. Review of recent literature on DSS and stochastic modeling

Functional Context	Mathematical Model and Solution Platform	Source
Decision Support System		
Cost architecture analysis in assembly systems	Integer linear program solved using IBM CPLEX OPL 12.6, automation in projects	[10]
Asset liability management modeling for life insurance company in India	Two-stage stochastic programming and Big data analytics based DSS	[11]
Marine and liner vessel fuel and speed optimization using weather archived data	Fuel consumption function for speed optimization a metaheuristic optimization approach	[12]
A two-stage stochastic programming approach		
Thermal power plant, and modeling electricity demand uncertainty, and wind speed	A two-stage stochastic program for optimal scheduling of energy storage system	[13]
Energy sector, uncertain energy prices, CO2 emission reduction	Two-stage stochastic mixed-integer programming approach	[14]
Value-based closed-loop supply chain network tactical and strategic planning	Three echelon, multi-commodity, multi-period two-stage stochastic program	[15]

Production, inventory and backordering cost reduction in manufacturing organizations	Two-stage stochastic programming for scheduling and lot-sizing under random demand, Solved using GAMS.	[16]
Retail staffing and employee scheduling in Switzerland	Two-Stage Stochastic Programming with simple recourse, MILP in uncertain demand environment simulation	[17]

There has been a series of attempts to design and develop the SLP based DSS (Table 1). The focus of most of them have only been towards the mathematical model, algorithmic power, rigor of research. *It is unlikely that the practicing executive with little knowledge of OR/MS can implement such solutions. Our research bridge this gap of academic research versus the applied research.* The study primarily focuses on modeling demand uncertainty using a two stage SLP based user friendly menu driven DSS. Experiments set have been developed to test the multi-scenario optimization-based DSS with data from an integrated steel company from North America. The experiments are designed by varying volatility in the market demand with probability of the possible economic scenarios.

3 OPTIMIZATION MODEL AND SCHEMA

There are six fundamental elements of the model's database structure, namely *Times, Scenarios, Materials, Facilities, Activities, Storage-Areas*. In line with the previous research by [4] Scenarios are added as an additional fundamental element [6]. They [6] discussed implementing a DSS in an SLP model, its detailed mathematical formulation, and the designed and developed database structure in their studies. The details of the model parameters, variables and the steps of optimization and model assumptions are referred to by [4, 18]. The model maximizes the expected contribution to a company's profit (nominal or discounted) subject to *Material Balance, Facility Input, Facility Output, Facility Capacity, Storage Inventory Balance, Storage Capacity, Set of Implementability (Non-Anticipativity) Constraints, and the Bounds on decision variables*. The model's objective and constraints are discussed in Appendix-A in brief to simplify understanding the context of the steel industry optimization application for this paper's audience.

4 DEFINING MODELS AND DESIGNING DEMAND SCENARIOS

Demand scenarios are designed based on the volatility in demand and change in probability of demand scenario occurrence (Table 2). Stochastic Optimization Model Instances: The detailed definition of various model instances is referred to [8]. The algebraic codes of the model instances are as follows: Perfect Information Solution

(Z_{PI}), Mean Value Solution (Z_{MV}), SLP Solution (Z_{SLP}), The expectation of Expected Value Solution (Z_{EEV}). Where:

$$VSS = (Z_{SLP}) - (Z_{EEV}); EVPI = (Z_{PI}) - (Z_{SLP})$$

Table 2. Definition of probability scenarios and demand cases

Probability Scenario Cases	Expected Economic Situation		
	LOW	REG	HIGH
Case i (Right Skewed)	0.75	0.15	0.10
Case ii (Equally Likely)	0.33	0.33	0.33
Case iii (Left Skewed)	0.10	0.15	0.75
Demand Cases	LOW	REG	HIGH
Case 1: 20 % Demand Volatility	80% of D	D	120% of D
Case 2: 30 % Demand Volatility	70% of D	D	130% of D
Case 3: 40 % Demand Volatility	60% of D	D	140% of D

5 DSS APPLICATION IN STEEL COMPANY

This study describes the application of the SLP model in a steel company. The steel company profile and the large-scale SLP optimization model are described in Table 3 and Fig. 1A. The optimal solution of SLP in steel company is shown in a user-friendly DSS layout in Fig 2.

Table 3. Characteristics of the industry and variability of optimization

Production Parameters		Model Parameters	
Annual Turnover (Mn US\$)	1,400	No of Variables	44100
Annual Production (Tons)	860,000	No of Constraints	40472
Sell Price Ratio	7.38	No of Coeff (Non-zeros)	168600
Market Demand Ratio	1,841.12	(LP Density – Nonzeros)	0.0094%
Buy Price Ratio	147.99	No of Materials	632
Facility Activity Ratio (T/H)	3,240.83	No of Facilities	56
Activity Cost Ratio (US\$ /Ton)	178.57	No of Activities	1286
		No of Planning Periods	3
		No of Scenarios	3

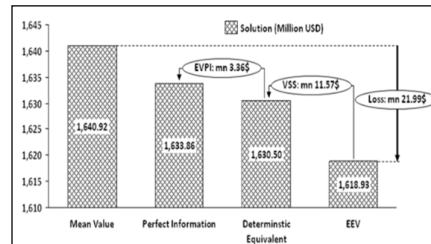


Figure 1A. Results of SLP model

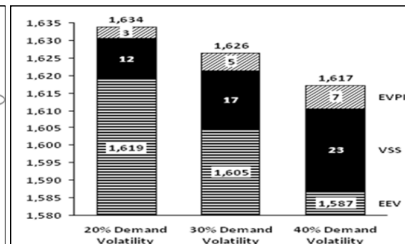


Figure 1B. SLP optimization results

Impact of SLP in the Steel Company

1. One would only solve an MV problem when the information about the future is not available and expect to achieve Z_{MV} (US\$ 1,640.9 million), while once the planning horizon is over, one would end up realizing only Z_{EEV} (US\$ 1,618.9 million). A loss of $(Z_{MV} - Z_{EEV})$ US\$ 21.99 million is incurred due to the non-availability of any information about the future.
2. The Z_{MV} is highest among all the solutions, namely Z_{MV} , Z_{PI} , Z_{SLP} , and Z_{EEV} . This indicates that practically Z_{MV} (US\$ 1640.9 million) can never be realized. In the long run, one can only realize the Z_{PI} (US\$ 1633.9 million) even with the availability of perfect information.
3. The impact of SLP is measured in terms of VSS (US\$ 11.6 million), the improvement in net (contribution to) profit by Z_{SLP} concerning Z_{EEV} . The VSS as a percentage of Z_{EEV} is 0.71%.
4. There are instances when it is possible to get perfect information about the future and know which scenario would occur with certainty. In these situations, it is expected to achieve a long-run solution as Z_{PI} (US\$ 1,633.9 million). When the information about the future scenario occurrence is partially available, Z_{SLP} (US\$ 1,630.5 million) can be attained. The expected value of perfect information is given by the difference between Z_{PI} and Z_{SLP} (US\$ 3.4 million).

Birge (1997) established the principles that a decreasing trend is observed in solutions ($Z_{MV} \geq Z_{PI} \geq Z_{SLP} \geq Z_{EEV}$) for a maximization SLP. Our results were consistent with these principles (Table 5).

Table 4. Equally likely scenario, 20% demand volatility

Planning Periods	Total Revenue	Cost of Purchases	Cost of Inv Carrying	Cost of Activities	Net Profit	Total Steel
Unit	Mn US\$	Mn US\$	Mn US\$	Mn US\$	Mn US\$	Mn Tons
Grand Total	3,295	801.3	121.1	742.4	<u>1,630.5</u>	2.18
Unit Basis	1510	367.2	55.5	340.2	747.2	NA
Scenario: L	1,080	266.5	40.4	244.2	529.3	2.19
Scenario: R	1,102	266.8	40.2	248.9	546.5	2.18
Scenario: H	1,112	268.0	40.5	249.3	554.6	2.18

Note¹

¹ Table should be replicated for a Cartesian product of demand variability of 20%, 30% and 40%, and the three probability distributions like left-skewed, equally likely, and right-skewed.

Table 5. Experiment results from multi-scenario planning (Mn means million)

Probability Distribution		Right Skewed (R)	Equally Likely (E)	Left Skewed (L)			
		Demand Volatility Cases					
		20%	40%	20%	40%	20%	40%
		M11	M3	M4	M6	M7	M9
PI	Mn \$	1605	1551	1633	1617	1658	1669
MV	Mn \$	1610	1567	1640	1640	1661	1679
SLP	Mn \$	1603	1548	1630	1610	1654	1661
EEV	Mn \$	1593	1523	1618	1587	1646	1644
VSS	Mn \$	10.6	24.6	11.6	23.4	7.6	16.2
VSS (% of EEV)	%	0.67	1.61	0.71	1.47	0.46	0.98
EVPI	Mn \$	1.5	2.8	3.4	6.7	4.5	8.8

Trend Analysis with Volatility in Market Demand: This section addresses questions 1 and 2 raised in the introduction section. The important inferences from different solutions due to a change in demand volatility from 20% to 40% are listed below: see Fig. 1B.

The experiments demonstrate that VSS, EVPI increases, and Z_{EEV} and total contribution of SLP decreases with increased volatility in finished goods demand; see Fig. 3A, 3B, and 3C. The results are consistent in the remaining experiments of probability skewness, i.e., right-skewed and left-skewed.

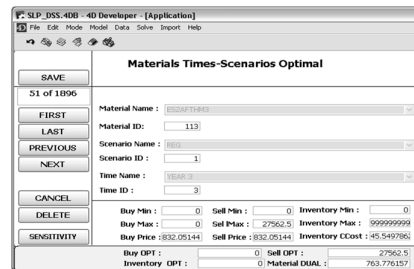


Figure 2. Optimal solution layout

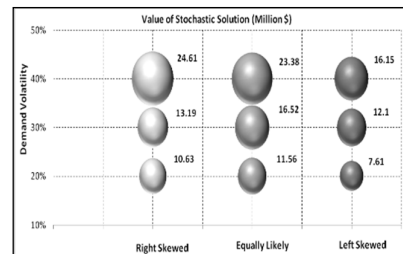


Figure 3A. VSS trend (demand volatility)

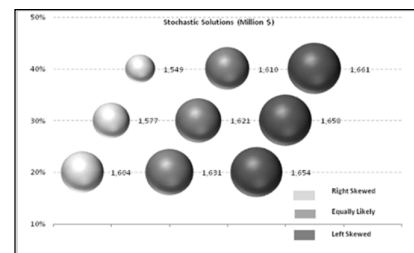


Figure 3B. SLP profit with demand

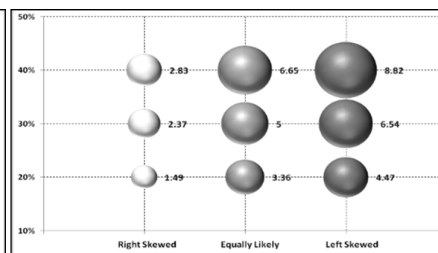


Figure 3C. EVPI with varied probability

Trend Analysis over Probability Distribution: This section addresses questions 3 and 4 raised in the introduction section. The VSS is the lowest with a left-skewed probability distribution. As the probability of a lower demand situation increases, the VSS increases (Fig. 3A). The impact of optimization on the VSS using SLP becomes more visible. Companies are more concerned about profits when the probability of low demand is high.

EVPI consistently increases with a variation in the discrete probability distribution from a right-skewed to a left-skewed demand situation (Fig. 3C). Fig. 3B clearly shows that the Z_{SLP} increases with the increasing probability of high demand situations (Right skewed to Left skewed distribution). The Z_{EEV} increases at a steeper rate than Z_{SLP} with the increase in the probability of high demand situations (i.e., Right skewed to left-skewed distribution). One may notice that when the probability of a low-demand situation is high, one plans for a Z_{MV} , but realizes Z_{EEV} . The difference in Z_{MV} and Z_{EEV} happens to be more due to incorrect first-stage decisions. The SLP corrects the first stage decisions so that the losses due to Z_{MV} expectations are minimized, and the VSS is maximized. When the high-demand situation occurs with a high probability of occurrence (left-skewed distribution), the Z_{EEV} starts approaching Z_{SLP} , and so the VSS in this situation is lower than the VSS in the right-skewed probability distribution.

6 CONCLUSION, LIMITATIONS, AND FUTURE DIRECTIONS

The necessity of stochastic optimization in the process industry is highlighted in this study for demand uncertainty of supply chain. We have witnessed unprecedented growth of Analytics that encompasses operations research, decision theory, statistics, computer science, and industry 4.0. Multi-stage optimization based on Stochastic Linear Programming (SLP) is a very useful concept in operations research. It has applications in the manufacturing industries like integrated iron and steel.

Applying the multi-scenario model in the DSS demonstrated a significant potential to improve the company's (contribution to) profit. A typical observation was that the profit from applying the SLP solution (in terms of VSS and EVPI) increases with the spread of demand distribution. Our results emphasize the need for SLP in an uncertain demand situation to improve profitability, especially when the occurrence probability of the low demand situation is very high. A consistent pattern in EVPI is observed; that is, EVPI is the highest when the occurrence probability of high demand is high (left-skewed) in each of the three demand cases, that is 20%, 30%, and 40%. Findings of the experiments obtained from this research, where we observed the pattern of VSS and EVPI with the change in the probability distribution of the demand, should be studied in various other industries. The DSS being generic, can be tested for modeling uncertainty in multiple input parameters simultaneously with various realistic probability distributions in various process industries. A Monte Carlo simulation in the SLP-based DSS for nonlinear or fuzzy LP applications may reveal interesting trends and inferences.

Appendix A: Outline of the SLP model from Gupta et al. (2018)

In order to avoid the repetition of the model formulation in the academic literature, but to improve the ready readability of the paper we present here a brief outline of the model published in Gupta et al., (2018) as follows.

Equation1: Nominal objective function

$$Z_N = \sum_{l \in L} p_l \sum_{t \in T} Z(l, t) \quad (1)$$

Where,

Equation 2: Objective function as a function of time and scenario

$$Z(l, t) = \sum_{j \in M} C_{jlt}^{sell} X_{jlt}^{sell} - \sum_{j \in M} C_{jlt}^{buy} X_{jlt}^{buy} - \sum_{j \in M} C_{jlt}^{inv} X_{jlt}^{inv} - \sum_{(j, j') \in M^{conv}} C_{jj't}^{conv} X_{jj't}^{conv} - \sum_{(i, k) \in F^{act}} C_{iklt}^{act} X_{iklt}^{act} - \sum_{i \in F} C_{ilt}^{cap} X_{ilt}^{cap} \quad (2)$$

The C and X represents the respective cost parameter, and decision variables. The subscript l, t, j, i, k indicates the set of scenarios, time horizons, materials, facilities, and activities respectively. Subject to the various material balance, facility input, facility output, facility capacity, storage inventory, storage capacity, set of implement ability (non anticipativity) constraints and bounds.

References

1. Fourer, R.: Database structures for mathematical programming models. Decis. Support Syst. (1997). [https://doi.org/10.1016/S0167-9236\(97\)00007-9](https://doi.org/10.1016/S0167-9236(97)00007-9)
2. Dutta, G., Fourer, R.: An Optimization-Based Decision Support System for Strategic and Operational Planning in Process Industries. Optim. Eng. (2004). <https://doi.org/10.1023/b:opte.0000038888.65465.4e>
3. Dutta, G., Fourer, R., Majumdar, A., Dutta, D.: An optimization-based decision support system for strategic planning in a process industry: The case of a pharmaceutical company in India. Int. J. Prod. Econ. (2007). <https://doi.org/10.1016/j.ijpe.2006.04.011>
4. Dutta, G., Fourer, R.: Database structure for a class of multi-period mathematical programming models. Decis. Support Syst. (2008). <https://doi.org/10.1016/j.dss.2008.02.010>
5. Dutta, G., Gupta, N., Fourer, R.: An optimization-based decision support system for strategic planning in a process industry: The case of aluminium company in India. J. Oper. Res. Soc. (2011). <https://doi.org/10.1057/jors.2010.8>
6. Gupta, N., Dutta, G., Fourer, R.: An expanded database structure for a class of multi-period, stochastic mathematical programming models for process industries. Decis. Support Syst. 64, (2014). <https://doi.org/10.1016/j.dss.2014.04.003>
7. Dutta, G., Gupta, N., Fourer, R.: An optimization-based decision support system for strategic planning in a process industry: The case of aluminium company in India. J. Oper. Res. Soc. 62, 616–626 (2011). <https://doi.org/10.1057/jors.2010.8>
8. Birge, J.R.: State-of-the-Art-Survey—Stochastic Programming: Computation and

- Applications. *INFORMS J. Comput.* (1997). <https://doi.org/10.1287/ijoc.9.2.111>
9. Dutta, G., Gupta, N., Mandal, J., Tiwari, M.K.: New decision support system for strategic planning in process industries: Computational results. *Comput. Ind. Eng.* 124, 36–47 (2018). <https://doi.org/10.1016/j.cie.2018.07.016>
 10. Salmi, A., David, P., Blanco, E., Summers, J.D.: A review of cost estimation models for determining assembly automation level. *Comput. Ind. Eng.* (2016). <https://doi.org/10.1016/j.cie.2016.06.007>
 11. Dutta, G., Rao, H. V., Basu, S., Tiwari, M.K.: Asset liability management model with decision support system for life insurance companies: Computational results. *Comput. Ind. Eng.* (2019). <https://doi.org/10.1016/j.cie.2018.06.033>
 12. Lee, H., Aydin, N., Choi, Y., Lekhavat, S., Irani, Z.: A decision support system for vessel speed decision in maritime logistics using weather archive big data. *Comput. Oper. Res.* (2018). <https://doi.org/10.1016/j.cor.2017.06.005>
 13. Daneshvar, M., Mohammadi-Ivatloo, B., Zare, K., Asadi, S.: Two-stage stochastic programming model for optimal scheduling of the wind-thermal-hydropower-pumped storage system considering the flexibility assessment. *Energy*. (2020). <https://doi.org/10.1016/j.energy.2019.116657>
 14. Mavromatidis, G., Orehounig, K., Carmeliet, J.: Design of distributed energy systems under uncertainty: A two-stage stochastic programming approach. *Appl. Energy*. (2018). <https://doi.org/10.1016/j.apenergy.2018.04.019>
 15. Badri, H., Fatemi Ghomi, S.M.T., Hejazi, T.H.: A two-stage stochastic programming approach for value-based closed-loop supply chain network design. *Transp. Res. Part E Logist. Transp. Rev.* (2017). <https://doi.org/10.1016/j.tre.2017.06.012>
 16. Ramaraj, G., Hu, Z., Hu, G.: A two-stage stochastic programming model for production lot-sizing and scheduling under demand and raw material quality uncertainties. *Int. J. Plan. Sched.* (2019). <https://doi.org/10.1504/ijps.2019.102993>
 17. Parisio, A., Neil Jones, C.: A two-stage stochastic programming approach to employee scheduling in retail outlets with uncertain demand. *Omega (United Kingdom)*. (2015). <https://doi.org/10.1016/j.omega.2015.01.003>
 18. Gupta, N., Dutta, G., Tiwari, M.K.: An integrated decision support system for strategic supply chain optimisation in process industries: the case of a zinc company. *Int. J. Prod. Res.* 56, 5866–5882 (2018). <https://doi.org/10.1080/00207543.2018.1456698>