Electricity Procurement for Large Consumers with Second Order Stochastic Dominance Constraints

M. Zarif*, M. H. Javidi* and M. S. Gazizadeh**

Abstract: This paper presents a decision making approach for mid-term scheduling of large industrial consumers based on the recently introduced class of Stochastic Dominance (SD)-constrained stochastic programming. In this study, the electricity price in the pool as well as the rate of availability (unavailability) of the generating unit (forced outage rate) is considered as uncertain parameters. The self-scheduling problem is formulated as a stochastic programming problem with SSD constraints by generating appropriate scenarios for pool price and self-generation unit's forced outage rate. Furthermore, while most approaches optimize the cost subject to an assumed demand profile, our method enforces the electricity consumption to follow an optimum profile for mid-term time scheduling, i.e. three months (12 weeks), so that the total production will remain constant.

Keywords: Electricity Procurement for Large Consumers, Second Order Stochastic Dominance, Decision making, Uncertainty.

1 Introduction

The purchase allocation problem is one of the most important problems which large electric energy consumers under market environments face as they need to reduce their production costs and risks to take the advantage of economic opportunities and to increase their profits. The cost of electricity, especially in cases where it serves as the main source of energy for industries, dominantly influences their production costs. Therefore, strategic plans resulting in the consumption of cheaper electric energy lead to higher profits.

The uncertainty and the volatility associated with electricity prices and the rate of availability (unavailability) of the generating unit (forced outage rate) make the process of optimizing the energy consumption from different energy sources more difficult and risky. This paper proposes a method to optimize the consumption of electric energy for industrial consumers based on the concept of stochastic dominance formulated in the form of a stochastic programming problem. The attractiveness of the SD is non-parametric, in the sense that its criteria do not impose explicit specifications of decision-maker preferences or restrictions on the functional forms of probability distributions and just rely on general preferences [1]. The SD (Stochastic Dominance) is a well-established concept in decision making theory and allows risk management from a different perspective to mean-risk approaches. The search for the best decision is replaced by seeking an acceptable decision and then optimizing over them [2, 3].

As another novelty, while most approaches optimize the cost subject to fixed amount of electricity consumption in each hour, this paper enforces the electricity consumption to follow an optimum profile for mid-term time scheduling, i.e. three months (12 weeks), so that the total production of the industry remains constant.

Several researches have been conducted on the problem of electricity procurement, which large consumers confront. Daryanian has proposed an approach to derive the consumer's reaction to spot prices in the electricity market [4]. The optimal demand for a consumer in a deregulated power market has been presented by Yan and Yan [5]. In [6], presenting a formulation which precisely models the price-maker capability of altering market-clearing prices, the self-scheduling problem for a price-maker is determined so that its profit is maximized. Kirschen has investigated the problem of medium-term profit maximization for retailers [7]. Liu has raised the problem of purchase allocation for dual electric power markets [8]. Modeling the sequential nature of purchase allocation by conditional stochastic characteristics and price volatility

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are explicitly considered in [8]. An optimization model for medium-term management of a thermal and electricity supply system for an industrial consumer under restructured electricity market has been presented in [9]. This model presents the optimal contracting decision by the minimization of the costs for overall annual energy supply. Conejo et. al. have provided a procedure that allows a large consumer to determine his optimal electric energy procurement supplied from different electricity sources, namely, bilateral contracts, the pool, and self-production [10]. In another work, Conejo et. al. have proposed a framework for electricity procurement by large consumers considering the risk associated to cost volatility [11]. In addition, the optimal amount of self-produced energy to be sold to the pool by the large consumer is determined. However, they did not consider uncertainties associated with the consumer's demand. Carrion et. al. have developed a decision-making technique based on the stochastic programming for electricity procurement by the large consumer who owns a self-generating facility [12]. They considered the risk aversion through the CVaR methodology. In the decision framework presented in [12], procurement of energy from different contracts is carried out at the start of each week. However, it seems that it should be more advantageous to decide on energy procurement according to prices during each week. In [11, 12], the availability of self-generating unit is not considered and the consumer's demand is also assumed to be known. As an alternative approach to stochastic programming, the Information Gap Decision Theory (IGDT) has also been utilized by Zare et al. [13, 14] for energy procurement problem. In IGDT the error between actual and forecasted values of uncertain parameters is modeled and no assumption on the structure of uncertain parameters is required. However, in the study conducted by Zare et al in [13, 14], only pool price uncertainties have been taken into account and Forced Outage Rate (FOR) of self-generation facility has been ignored. Furthermore, since IGDT models the error between actual and forecasted parameters, it seems it cannot model the FOR of the self-generation facility.

This paper focuses on developing a decision making tool for mid-term planning problems which large industrial consumers face, subject to the volatility of electricity price, and the rate of availability (unavailability) of the generating unit (forced outage rate). Significant contributions of this paper are summarized as follows:

1. Considering and minimizing the risk by minimization of electricity procurement from market, subject to (SSD).
2. Optimization of the hourly demand profile assuming that the consumer's load profile is unknown.
3. Introduction of the risk factor γ in the SSD constraint which helps to reflect the level of the risk-aversion.
4. Analyzing the impact of the self-generation forced outage rate (FOR) on the procurement from the pool, contracts and the self-generation.

It's also worth highlighting that in the proposed stochastic programming approach based on the SSD constraints, to different objective functions can be considered. In fact, SSD-constrained stochastic programming formulation allows us to consider two different functions as the objective function and in the SSD constraints. Hence, a different function other than cost or profit, which better reflect the preference of the decision-maker, can be used as the objective function and economic issues, e.g. cost or profit optimization, can be done through the SSD constraint and using a pre-determined benchmark profile.

The paper is organized as follows: The SSD Constrained Stochastic Programming is introduced in section 2. Section 3 formulates and characterizes the decision-making problem for minimization of procurement through markets subject to the second order stochastic dominance (SSD). Simulation results are presented in section 4. Finally, section 5 presents conclusions.

2 SSD Constrained Stochastic Programming

2.1 Multi Stages Stochastic Programming

When decisions are made based on certain circumstances, the decision-maker may adopt the decision confidently. On the other hand, when uncertainties prevail, the decision-making problem turns to a challenging task. In real world, decision-making processes often encounter uncertainty and vagueness of information and data. Stochastic programming, established based on the probability theory, has found many applications in linear programming in the optimization of problems involving uncertain information and data [15, 16]. In this paper, multi-stage stochastic programming approach has been utilized for the minimization of procurement from the market. The second order stochastic dominance has been adopted as the ranking method. The consumer's hourly demand profile over the planning horizon has determined, and procurement is done from available energy sources, including electricity pool, bilateral contracts and a limited capacity self-generation facility, while the energy procurement cost is enforced to stochastically dominate a reference profile.

2.2 Concept of Stochastic Dominance

Mean-risk approaches consider the risk measure by adding a weighing term related portion as the risk measure to the original objective function. This may lead to a linear compromise between risk and the original objective function, which may not be suitable in all circumstances. Furthermore, according to some findings, the mean-risk models are not capable of modeling the entire gamut of risk-averse preferences [16]. A major challenge in using the optimization to risk-averse decision-making in the case of uncertainties is how to specify an acceptable level of risk. On the other hand, stochastic optimization with Stochastic Dominance (SD) constraints, proposed by Dentcheva and Ruszczynski [17], tries to find an answer which is suitable (i.e. Acceptable with respect to a reference decision) but more prospective, i.e. less risky. Based on this idea, the decision maker should first specify a reference decision and then find the optimal solution of the problem subject to a constraint enforcing the selected outcome to stochastically dominate the reference decision.

The main theme of stochastic dominance relies on the fact that, when a decision maker has to choose between two actions with uncertain consequences, he will choose the one which promises higher possibilities [3]. In this paper, a more detailed discussion on the concept of SSD, and its mathematical formulation, where smaller outcomes are preferred, are presented.

Definition 1 [17]: Random variable X is said to be stochastically dominating random variable Y in the second order in terms of smaller outcome ($X \geq_2 Y$) if,

$$\int_{-\infty}^{\eta} F_x(\eta) \geq \int_{-\infty}^{\eta} F_Y(\eta), \forall \eta \in R \quad (1)$$

Proposition [17]: Let y_k with $k = 1, 2, \ldots k_d$ be the realizations of reference variable Y, then the above equation is equivalent to,

$$E\left(y_k - X\right)_+ \geq E\left(y_k - Y\right)_+, k = 1, \ldots k_d \ \ldots \ \ldots\ldots \quad .(2)$$

where, $(.)_+$ means max(0, .).

If it is intended to reflect the level of risk-aversion of a large consumer, definition 1 will be unsatisfactory. To overcome this shortcoming, we propose the concept of γ-constraint stochastic dominance, as presented in definition 2 that could help us (to) reflect the level of risk-aversion.

Definition 2: (γ-constrained stochastic dominance): Let y_k and with $k = 1, 2, \ldots k_d$ be the realizations of reference variable Y, then we define γ-constrained second order stochastic dominance as,

$$E\left(\gamma \times y_k - X\right)_+ \geq E\left(\gamma \times \left(y_k - Y\right)\right)_+, k = 1, \ldots k_d \ \ldots .(3)$$

Most practical decision problems involve a sequence of decisions that react to outcomes that evolve over the time. A variety of models i.e. chance-constrained models, two- and multi-stage models, models involving risk measures have been developed by stochastic programming theory to handle the presence of random data in the optimization of such problems [15]. We will consider the stochastic programming approach for these multistage problems.

The stochastic programming problem subject to second order stochastic dominance constraint can be stated as:

$$Min\ \left(E[H(X)]\right), s.t\ X \leq_2 Y, X \in X_0 \ \ldots\ldots\ldots \quad \ldots\ldots..(4)$$

where, X is the decision vector, Y is the reference decision and $H(X)$ is the objective function [18]. In this paper, to compute the value of $E[H(X)]$, we use finite realization of random variable X, known as scenarios. The pool price and availability of self-generation facility constitute the randomness of our decision-making problem.

2.3 Scenario Generation

Various methods have been developed for scenario generation in stochastic optimization. Scenarios may be generated by sampling time series or statistical models [19]. In this paper, Monte-Carlo simulation is employed to generate market price and availability of unit scenarios. In this approach, it is assumed that predictions on market price and its variance are available. These are produced by using time series forecasting methods. Then, Monte-Carlo simulation is carried out for a large number of iterations (say M) to generate scenarios with equal probability for the price (equi-probable price scenarios). It must be noted that the Monte-Carlo simulation is applied for each period separately and may lead to coupling information at consecutive periods [20].

In case of unit's FOR we use the following equations, as stated in [21], for statistical modeling of availability of self-generation facility,

$$\lambda_f = -MTTF \times ln(u_a) \quad (5)$$

$$\mu_r = -MTTR \times ln(u_b) \quad (6)$$

where λ_f and μ_r are mean time between failures and mean time to repair respectively. u_a and u_b are random variables uniformly generated in the range of [0 1].

A large number of generated scenarios hinder finding a solution to the stochastic optimization. Hence, applying a proper scenario reduction technique seems inevitable. Accordingly, we use the scenario reduction technique proposed in [21-22], which is developed based on the idea of eliminating scenarios with lower probability and bundling close scenarios. A probability measure is used to compute the distance between scenarios, then the scenario reduction technique creates a sub-set of price scenarios. It must be noted that in the case of unit availability scenario, due to the presence of binary variables, the probability measure is not applicable. Therefore, we have used the idea presented in [23] for the reduction of scenarios of unit availability. The probabilities for reduced scenarios are so calculated that the reduced probability metrics are closest to the original probabilities [21].

3 The Structure of the Proposed Approach

Large industrial plants, as energy consumers, commonly include several production units in their production process chain. Each unit may have its own technical limitations such as rated capacity, minimum time to be in service, etc. The typical structure of an industrial consumer, in addition to production units, normally includes some reservoirs as illustrated in Fig. 1. In this figure, the production line is assumed to be composed of four production units along with three reservoirs. The proper economically- and technically-efficient production scheduling is of crucial importance for every industrial producer. A cost-effective planning for an industrial producer should determine the production pattern of producing units, while the technical restrictions are taken into account for a given production level over a planning horizon.

We restrict our study to a cement producing complex with four production lines, each composed of four units including, the crusher (CR), the raw mill (RM), the kiln (KL) and the cement mill (CM) [24]. The produced material at each stage can be directly sent to the next production unit, or may be stored in storing facilities, ST_1 to ST_3, for future usage. The input material for each production unit can be directly provided from the previous stage or may be received from the reservoir. The required electricity for production units may be supplied by either one of three different sources or a combination of them, namely, the electricity market, bilateral contracts and self-production facility.

3.1 Decision Framework

We consider a situation where the industrial consumer has to decide upon an optimal procurement and hourly demand profile with partial information about the data involved, i.e. the market price and the availability of the self-generation unit. Implicitly, it is known that the procurement from bilateral contract has to be determined prior to the realizations of pool price and availability of the self-generation unit. It is also known that procurement from pool, self-generation and the hourly demand profile, as the recourse action, allow us to observe the future (through realization of the scenarios) and the selection of bilateral contracts. Therefore, a multi-stage dynamics of decision and observation problem emerges. In our approach, we first select bilateral contracts. Then procurement from

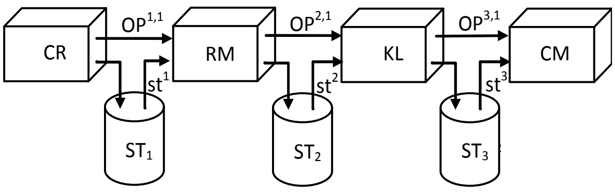

Fig. 1. Production diagram of an industrial consumer with 4 production units and 3 storing facility.

selected contracts, self-generation and the hourly demand profile shaping are carried out through realization of pool price and availability of the self-generation unit.

In our proposed framework, decisions made for procurement of energy in the first week of each month consists of 2 stages, while decisions for procurement of energy for any other week are carried out in one stage only; therefore a five-stage stochastic programming problem is implemented. The sequence of decision framework for each month is as follows:

Stage 1: Selection of contracts used during the first week.

Stage 2: Energy procurement from contracts, pool and self-generation during the week, shaping hourly demand profile during the first week and selection of contracts used during the second week.

Stage 3-5: Stage 2 continuing similarly to the other weeks up to the last (fourth) week.

3.2 Problem Formulation

In our approach, we are trying to minimize the purchase from the pool subject to SSD and the other operational constraints of the industrial consumer. For this purpose, first the minimum cost for procurement of required energy from available energy sources is derived as the reference profile. Then the acceptable decision (i.e. minimization of purchase from the pool) with respect to the reference profile and the risk factor γ is obtained by means of SSD-constrained stochastic programming. The mathematical formulation for the stochastic minimization of the purchase from the pool with recourse is stated by Eq. (7).

$$minimize \sum_{k\in N_T}\sum_{t=1}^{T} p_k \lambda_{t,k}^{m} P_{t,k}^{m} \tag{7}$$

$$s.t.$$

$$SSD_1 : y_l - f\left(X_k\right) \le z_{l,k} \tag{8}$$

$$SSD_2 : \sum_{k=1}^{N_T} p_k z_{l,k} \le \bar{a}_l \tag{9}$$

$$\bar{a}_l = E\left[\max\left(0, y - \gamma \times y_l\right)\right], l = 1,2,......,L, z_{l,k} \ge 0, \\ X_k \in R \tag{10}$$

Constraints in Eqs. (8)-(10) are related to the calculation of SSD. These constrains formulate the calculation of the SSD in terms of generated scenarios [17]. The parameter γ sets the level of risk-aversion by the consumer. In constraint (8) and (9), the SSD equation controls the excess of cost over the reference profile. The parameter γ in Eq. (10) can be interpreted as the excessive cost (with respect to the reference profile of cost) which the decision-maker tolerates to achieve a more reliable decision and is always larger that one. The upper bound on parameter γ is set through the risk-preferences of the decision maker. For instance a value of 1.1 for γ means that the decision maker is sacrificing 10 percent of its reference cost to get more reliability. Based on the presented discussion, the smaller values of γ correspond with the more risky behavior of the consumer and vice-versa.

$$f\left(X_k\right)=\sum_{t=1}^{T}\lambda_{t,k}^{m}P_{t,k}^{m}+\sum_{i\in I}\sum_{t=1}^{T}\lambda_{i,t,k}^{c}P_{i,t,k}^{c}+\sum_{t=1}^{T}C_{t,k}\left(P_{t,k}^{SG}\right) \tag{11}$$

$$\lambda_{i,t,k}^{c}=\frac{\lambda_{t,k}^{m}+\lambda_{t,i}^{c}}{2} \tag{12}$$

The cost function in constraint (11) is composed of three terms expressing the costs incurred by the pool, bilateral contracts and self-generation units respectively.

In Eq. (12) the price of bilateral contracts is defined as the average value of two components; one of which is the market price and the other one is a constant component (price) as stated in [12]. The production cost of the self-generation facility is expressed by a three-block piecewise linear function [12]. The piecewise linear production cost of the self-production unit is modeled as Eq. (13).

$$C_{t,k}\left(P_{t,k}^{SG}\right)=\begin{cases} MC_1\times P_{t,k}^{SG} & if \quad P_{t,k}^{SG}\le E_1 \\ MC_1\times E_1+MC_2\times\left(P_{t,k}^{SG}-E_1\right) & if \quad P_{t,k}^{SG}\le E_2 \\ \left(\sum_{u=1}^{u_{t,k}^{b}-1}MC_u\times E_u\right)+MC_{u_{t,k}^{b}}\times\left(P_{t,k}^{SG}-E_{u_{t,k}^{b}-1}\right) & if \quad P_{t,k}^{SG}\le E_{u_{t,k}^{b}} \\ \left(\sum_{u=1}^{u_{t,k}^{b}-1}MC_u\times E_u\right)+MC_{n_b}\times\left(P_{t,k}^{SG}-E_{n_b-1}\right) & if \quad P_{t,k}^{SG}\le E_{n_b} \end{cases} \tag{13}$$

Also, contract contraints are as follows:

$$P_i^{e,\min}\le\sum_{t\in T_i}P_{i,t,k}^{c}\le P_i^{e,\max} \tag{14}$$

$$P_{i,t,k}^{c}=0 \quad if \quad t\notin T_i \tag{15}$$

$$0\le P_{i,t,k}^{c}\le P_i^{\max} \tag{16}$$

The maximum and minimum levels of purchased energy from bilateral contracts are stated by constraint (14). Constraint (15) implies that the purchase of energy through contract *i* can only be made during its validity period T_l . Constraint (16) imposes the maximum power that can be supplied through contract *i* in each period.

Self-Generation contraint is as follows:

$$0\le P_{t,k}^{SG}\le U_{k,t}\times E^{SG,\max} \tag{17}$$

Constraint (17) shows the generation limits of the self-generation unit.

Industrial consumer's constraints are as follows:

$$U_{k,t}\times P_{t,k}^{SG}+P_{t,k}^{m}+\sum_{i\in I}P_{i,t,k}^{c}=\sum_{n}KWhT_n\times\left(op_t^{n,1}+op_t^{n,2}\right), \quad n=\{CR,RM,KL,CM\} \tag{18}$$

$$r_{n+1}\times\left(op_t^{n,1}+sto_t^{n}\right)=op_t^{(n+1),1}+stin_t^{n+1} \quad n=CR,RM,KL \tag{19}$$

$$op_t^{n,2}=stin_t^{n} \tag{20}$$

$$st_t^{n}\le st^{n,\max} \tag{21}$$

$$op_t^{n,1}+op_t^{n,2}\le op^{n,\max} \tag{22}$$

$$st_t^{n}=st_{t-1}^{n}+stin_t^{n}-sto_t^{n}, \quad n=CR,RM,KL \tag{23}$$

$$st_0^{n}=st_{n0} \tag{24}$$

$$P_t^{d}=op_t^{n,1}+op_t^{n,2},\ n=CM \tag{25}$$

$$\sum_{t=1}^{T}P_t^{d}=P_{total}^{D} \tag{26}$$

Constraint (18) states that the sum of supplied demands by the pool, bilateral contracts and self-generation must always be equal to the demand of the consumer.

Based on the constraint (19) the amount of input materials to each unit must be equal to the amount of the output materials, considering factor r_n , where in this equation, the factor r_n for a unit is defined as the ratio of the weight of output materials to the weight of input materials. Constraint (20) states that the second output of a unit is sent to the corresponding storing facility. Constraint (21) sets the maximum storing capacity of the storing facilities. Constraint (22) bounds the production rate of every unit. Constraint (23) defines the remaining amount of materials in the storing facilities. Constraint (24) sets the initial volume of the storing facilities. Constraint (25) states the final production of the factory a time *t*. The total production intended by the industrial consumer is set by constraint (26).

The above mentioned problem is solved by a stochastic mixed-integer programming with recourses. It is solved by using CPLEX with GAMS software [25]. So far, attention has not been paid to operational constraints as detailed as in our approach. The optimization problem consists of 772594 variables including real, binary and integer variables.

4 Case Study

To evaluate the proposed approach, we used it to find the optimum decision to supply the required electricity during a 3 months planning horizon. The electricity pool prices have been obtained by using average prices of energy sold to Iranian Electricity Market by electric utilities located in our region (Khorasan Province). It should be mentioned that Iranian Electricity Market is a pool based whole sale electricity market. In this market, utilities are paid for the capacity they offer as well as for electricity admitted on a pay as bid clearing mechanism.

4.1 Data

The technical parameters of cement producing units are presented in Table 1. Related parameters of self-generation facility for piece-wise linear cost model are given in Table 2.

Based on the idea presented in [12], each day has been divided into three periods, namely peak, shoulder and valley, as follows, Valley = {1, 2, 3, 4, 5, 6, 7, 8}, Shoulder = {9, 10, 15, 16, 17, 18, 23, 24}, Peak = {11, 12, 13, 14, 19, 20, 21, 22}.

Three bilateral contracts for the three daily time periods are assumed. These contracts are referred as; peak (*P*), shoulder (*S*) and valley (*V*) contracts. Each contract is specified by its duration, minimum and maximum levels of energy consumption and the contracted price for electricity during the period. In our simulations, the contracted period is assumed to be one week. Table 3 shows limitations for energy consumption in bilateral contracts during the contract period.

Table 1 Technical data for production units of the cement plant.

Process	CR	RM	KL	CM
rated consumption	2000	10000	10500	10200
$KWhT_n$ ($KWh.Ton^{-1}$)	1.5	31	23	37
Min_op_n ($Ton.h^{-1}$)	0	0	110	0
Max_op_n ($Ton.h^{-1}$)	800	300	125	200
r_n	1	1.2	0.6	1.04
$St^{n,max}$	22000	15000	50000	17600

Table 2 Production cost of the self-generating facility.

E_1 (MW)	E_2 (MW)	$E^{SG,max}$ (MW)	MC_1 ($\$.MW^{-1}$)	MC_2 ($\$.MW^{-1}$)	MC_3 ($\$.MW^{-1}$)
30	45	60	29	32	35

Table 3 Consumption limits of bilateral contracts (MWh).

Contract	$P_i^{e,min}$	$P_i^{e,\max}$	P_i^{max}
Peak	1050	3500	350
Shoulder	775	2950	30
Valley	550	2570	265

The uncertainties of pool price and unit availability are modeled by using scenarios described in section 2.3. The electricity prices of the mainland Spain market are used for scenario generation in this paper [26]. Each price scenario involves 252 price values over the study horizon. We consider 200 scenarios for pool price and then apply the scenario reduction technique to reduce the number of price scenarios. Then, the optimization problem is executed for different numbers of reduced scenarios as far as a significant change (e.g. 5%) appears in the objective function. In this paper, we reduced the number of price scenarios to 20.

To consider the unavailability of units, we generated 1000 initial scenarios and then reduced them to 25 scenarios. Then, the price and availability scenarios have been merged to produce 500 scenarios to solve the stochastic problem defined by the Eqs. (7)-(24).

Before solving the main problem with SDD constraints, we need to generate reference profiles. In order to derive this profile, we first run an expected cost optimization program with 500 price and unavailability scenarios generated earlier. Then, we use the optimal solution found by the optimization process and select 20 benchmark values using a clustering technique presented in [27]. The probability of each benchmark value is computed as the sum of probabilities of the members in its cluster. This procedure is repeated for unavailability values of 0, 0.02, 0.04, 0.06, and 0.08.

4.2 Results

To investigate the impact of the consumer's risk aversion on electricity procurement, various simulations were executed with different values of γ, including 1.01, 1.02, 1.05, 1.08, and 1.1, and values of FOR including 0, 0.02, 0.04, 0.06, and 0.08. Multiplying the benchmark profile by different values of γ, new benchmark profiles are generated. This way, for each value of unavailability, five different benchmark profiles will be generated. These profiles can be used to analyze the impact of factor γ and unavailability on demand allocation problem. Figs. 2 and 3 show the Cumulative Distribution Function (CDF) of benchmark profiles and the corresponding cost profiles for FOR = 0 and second and fifth benchmarks for this value of unavailability, respectively. It is clear from these Figures that the benchmark 5 has higher cost but less restrictive than the benchmark 2. The expected cost in the case of benchmark 2 is 3.18 million dollars while this value is 3.43 million dollars in the case of benchmark 5.

For a more detailed analysis on performance of the proposed strategy, the procurements from the pool, the self-generation and contracts during different periods are depicted in Figs. 4 and 5. Clearly, due to lower prices of electricity during valley hours, large portions of the demand are shifted to these hours. It is worth mentioning that, in contrast with procurement from the pool, the procurements from the self-generation and contracts have been used more frequently during shoulder and peak periods than that during valley hours. This is mainly due to the higher variations of the pool price during these periods, leading to more uncertainties.

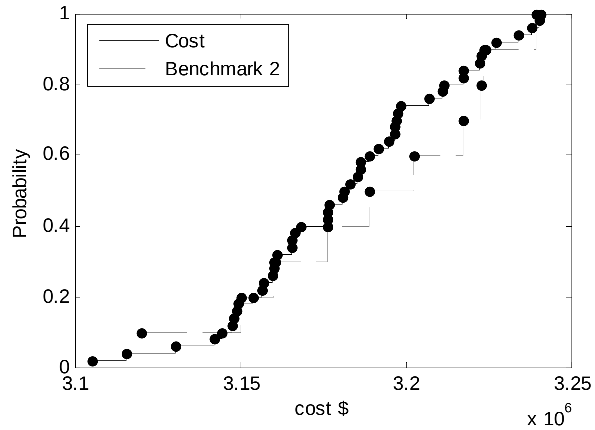

Fig. 2 Cumulative distribution function (CDF) of benchmark 2 (γ= 1.02).

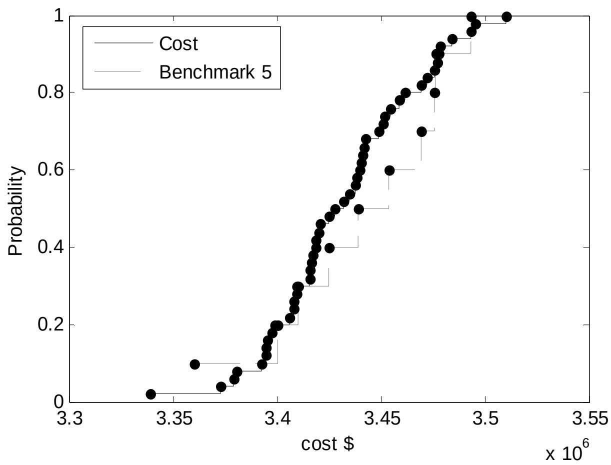

Fig. 3 Cumulative distribution function (CDF) of benchmark 5 (γ = 1.1).

Furthermore, as shown in Fig. 4, by increasing γ the use of bilateral contracts increases. This work results in a more robust and stable situation of the consumer. Therefore, it can be concluded that increase in value of γ results in robustness and reliability of the consumer. In fact, larger values of γ allows higher procurement costs in return for higher robustness against pool price variations.

Analyzing the energy procurement through contracts during the first and the third months, as shown in Fig. 6, shows another interesting result. Based on this figure, the procurement from contracts in the first month is higher than the last month. This result can be explained by using Fig. 7 taking into account the prices of the first and third months, we can obviously that state the prices of energy supplied through contracts and that supplied through pool are closer to each other as compared with those prices in the third month. Hence, a larger portion of procurement from contracts has happened in the first month.

Shaping the hourly demand is another important goal of our decision making tool. The results for this task are presented in Table 4, implying that a considerable portion of production has been shifted to valley and shoulder periods.

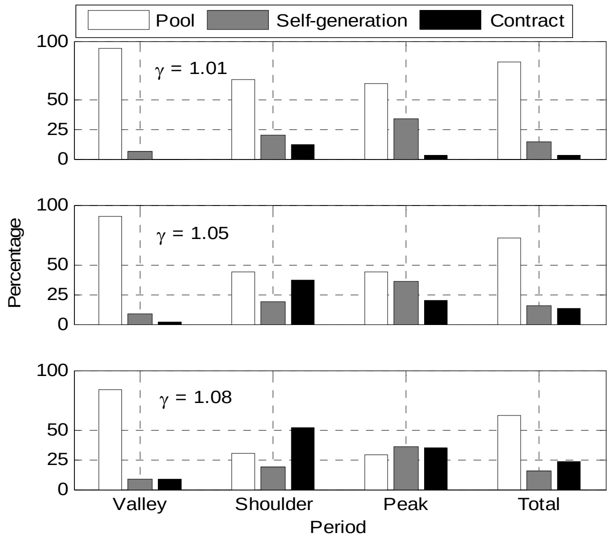

Fig. 4 Procurement of electricity from pool, bilateral contracts and self-generation for different γ 's and F.O.R.=0.

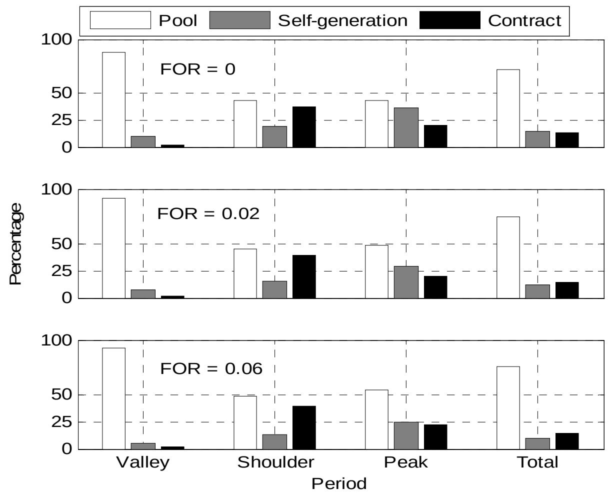

Fig. 5 Procurement of electricity from pool, bilateral contracts and self-generation for different FORs and γ =1.05.

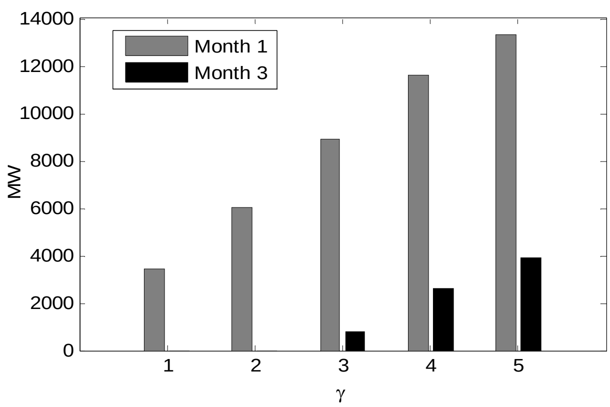

Fig. 6 Procurement from contracts in the first and third months.

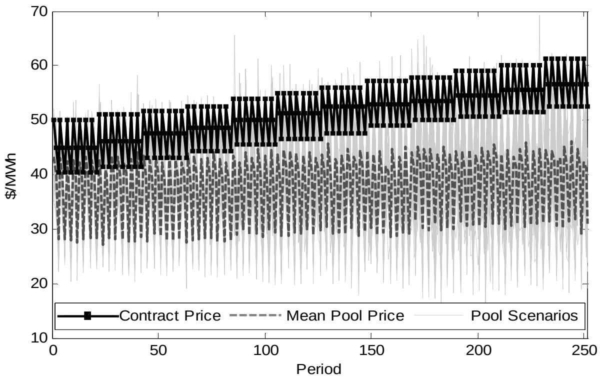

Fig. 7 Pool and contracts prices.

Table 4 Production of different units during different periods (*ton*).

Unit / Period	CR	RM	KL	CM
Peak	23.7	7029.7	6250.5	1642.2
Shoulder	70.7	13793	6387.6	4460.4
Valley	1722.5	24221	7414.6	27464

5 Conclusion

This paper presented a SSD-constrained stochastic programming approach for mid-term self-scheduling problem, faced by large industrial consumers. In contrast to the most published studies, which consider a fixed demand profile for the consumer, in the proposed approach demand profile optimization was also conducted, as it is highly incentivized by electric utilities. In the proposed decision making approach, based on the SSD constrained stochastic programming, we aimed at minimization of the cost of energy purchase from pool subject to SSD constraints. The SSD constraints provide decisions which are more probable compared to the given benchmark decision, i.e. the expected cost. Furthermore, a risk factor was introduced into SSD constraints to account for the level of risk-aversion of the consumer. The simulation results for a cement-producing complex confirm the validity of the proposed method in the electricity procurement problem to create an optimal demand profile. The proposed decision making framework can be employed by consumers to decide on energy procurement in market environment as well as following the demand optimization.

Appendix

Nomenclature

Since there are large numbers of variables, functions etc. throughout the paper, the descriptions of all notations are summarized in this section.

Real variables

E_u	Total output of self-generation unit up to unit *u* (*MWh*)
$op_t^{n,1}$	Output of unit *n* fed into unit *n+1* at time *t* (*ton*)
$op_t^{n,2}$	Output of unit *n* fed into store *n* at time *t* (*ton*)
$stin_t^n$	Input of store *n* to unit *n* at time *t* (*ton*)
$P_{i,t,k}^c$	Procurement from contract *i* for scenario *k* (MWh)
P_t^d	The final production of the consumer at time *t* (*ton*)
$P_{t,k}^m$	Procurement from market for scenario *k* and time *t* (MWh)
$P_{t,k}^{SG}$	Procurement from self-generation for scenario *k* at time *t* (MWh)
st_t^n	Stored material in store *n* at time *t* (*ton*)
sto_t^n	Output of store *n* to unit *n+1* at time *t* (*ton*)
X_k	Optimal procurement for scenario *k*

Stochastic Variables

$\lambda_{t,k}^m$	Market price for time *t* and scenario *k* (*$/*MWh)
λ_f	Time between two consecutive unit failures (*hour*)
μ_r	Repair time of unit (*hour*)

Binary Variables

u_a	Random variable related to mean time to failure
u_b	Random variable related to mean time to repair
$U_{t,k}$	Self-generation availability at time *t* and scenario *k*

Constants

$\bar{a}_l$	A probability used in stochastic dominance constraint related to l^{th} realization of reference cost
$E^{SG,\max}$	Maximum capacity of self-generation unit (MWh)
$KWhT_n$	The required energy for production of one tone of output by production unit *n* (*KWh/ton*)
MC_u	Marginal cost of block *u* of self-generating unit (*$.*MWh^{-1})
MTTF	Mean time to failure (*hour*)
γ	Proposed risk-aversion factor used in stochastic dominance constraint
$\lambda_{t,i}^c$	Deterministic price for contract *i* at time *t* (*$/*MWh)
$\lambda_{t,i,k}^c$	Contract price for time *t* and contract *i* in scenario *k* (*$/*MWh)
p_k	Probability of scenario *k*
r_n	The ratio of output material to input material of unit *n*
MTTR	Mean time to repair (hour)
$P_i^{e,\min}$	Minimum amount of energy for contract *i* (MWh)
$P_i^{e,\max}$	Maximum amount of energy for contract *i* (MWh)
$op^{n,\max}$	Rated capacity of unit *n* (*ton/hour*)
P_i^{max}	Maximum energy that can be supplied by contract *i* in one period (MWh)
$st^{n,\max}$	Maximum capacity of store *n* (*ton*)
Max_op	Maximum operational capacity of unit *n* (*ton/hour)*

Min_op	Minimum operational capacity of unit *n* (*ton/hour)*
y	Reference profile of cost (*Dollar*)
P^{D}_{total}	Total demand of large industrial consumer in scheduling horizon (MWh)
y_l	l^{th} Realization of reference expected cost (*Dollar*)
st_{n0}	Initial capacity of store *n* (*ton*)

Numbers

L	Number of reference profile
N_c	Number of bilateral contracts
T	Schedule period (252 periods)
N_p	Number of initial price scenarios
N_{pr}	Number of reduced price scenarios
N_f	Number of initial availability scenarios
N_{fr}	Number of reduced availability scenarios
N_T	Total number of scenarios
$u^{b}_{t,k}$	Number of self-generation blocks used in scenario *k,* at time *t*
n_b	Number of blocks of self-generation unit

Set

X_0	Set of feasible decisions
I	Set of bilateral contracts
T_i	Validity periods for contract *i*

Index

k	Scenario index
l	Index of Reference Expected cost
i	*Contract index*
u	Index of self-generation blocks
t	Period index
n	Units in their production process

Function

Pr_x	Probability distribution function of random variable *x*
F_x	Cumulative distribution function of random variable *x*
$E(x)$	Expected value of random variable *x*
$C_{t,k}(P^{SG}_{t,k})$	Self-generation cost for scenario *k at time t*
$f(X_k)$	Cost of scenario *k* (*Dollar*)
$H(X)$	Objective function used in definition of SSD-constrained stochastic programming
X, Y, η	Random variables used in definition of SD and SSD-constrained stochastic programming

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