

A single-item capacitated lot-sizing problem with stochastic demand under service level

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1 Joint chance-constrained programming model

We consider the single-item single capacitated lot-sizing problem. We present the deterministic variant of this problem which can be formulated as a mixed integer linear program (MILP). We model the problem using the general model and the aggregate formulation. We then consider a stochastic variants of this problem where the customer demand to be satisfied is subject to uncertainty and introduce the joint chance constrained programming formulation studied in the present paper.

2 Mathematical models

2.1 Deterministic models

We wish to plan production for a single product to be processed on a single capacitated resource over a planning horizon involving T periods indexed by $t = 1 \dots T$. All problem parameters are assumed to be deterministically known at the time when the production plan is built. f_t denotes the fixed setup cost to be paid if production occurs on the resource in period t , h_t the inventory holding cost per unit held in stock at the end of period t and c_t the production capacity available in period t . d_t is the demand to be satisfied at the end of each period t and $dc_t = \sum_{t'=1}^t d_{t'}$ is the cumulative demand over interval $[1; t]$. The initial inventory level, I_0 , is set to 0 without loss of generality. We introduce the following decision variables:

- x_t : the quantity produced in period t .
- $y_t \in \{0, 1\}$: the resource setup state in period t . $y_t = 1$ if a setup occurs in period t , 0 otherwise.
- I_t : the inventory at the end of period t

The first deterministic single-item single-resource capacitated lot-sizing problem can be formulated as follows (M_1):

$$\min \sum_{t=1}^T f_t y_t + \sum_{t=1}^T h_t I_t \quad (1)$$

$$x_t \leq C y_t \quad \forall t \in 1, \dots, T \quad (2)$$

$$I_{t-1} + x_t = d_t + I_t \quad \forall t \in 1, \dots, T \quad (3)$$

$$x_t, I_t \geq 0 \quad \forall t \in 1, \dots, T \quad (4)$$

$$y_t \in \{0, 1\} \quad \forall t \in 1, \dots, T \quad (5)$$

The second model using the aggregate formulation as follows (M_2):

$$\min \sum_{t=1}^T f_t y_t + \sum_{t=1}^T h_t \left(\sum_{t'=1}^t x_{t'} - d c_t \right) \quad (6)$$

$$x_t \leq C y_t \quad \forall t \in 1, \dots, T \quad (7)$$

$$\sum_{t'=1}^t x_{t'} = d_t \quad \forall t \in 1, \dots, T \quad (8)$$

$$x_t \geq 0 \quad \forall t \in 1, \dots, T \quad (9)$$

$$y_t \in \{0, 1\} \quad \forall t \in 1, \dots, T \quad (10)$$

2.2 Stochastic models

2.2.1 Classical formulation

$$\min \sum_{t=1}^T f_t y_t + \sum_{t=1}^T h_t I_t \quad (11)$$

$$x_t \leq C y_t \quad \forall t \in 1, \dots, T \quad (12)$$

$$Pr(I_{t-1} + x_t - I_t \geq d_t; \quad \forall t \in 1, \dots, T) \geq 1 - \alpha \quad (13)$$

$$x_t, I_t \geq 0 \quad \forall t \in 1, \dots, T \quad (14)$$

$$y_t \in \{0, 1\} \quad \forall t \in 1, \dots, T \quad (15)$$

The obtained stochastic linear model (SM_1):

$$\min \sum_{t=1}^T f_t y_t + \sum_{t=1}^T h_t I_t \quad (16)$$

$$x_t \leq C y_t \quad \forall t \quad (17)$$

$$I_{t-1} + x_t - I_t \geq z_t; \quad \forall t \quad (18)$$

$$\sum_t \sum_{j=d_t(min)}^{d_t(max)} z_{jt} \log(F_t(j)) \geq \log(1 - \alpha) \quad (19)$$

$$\sum_{j=d_t(min)}^{d_t(max)} z_{jt} = 1, \quad \forall t \quad (20)$$

$$z_t = \sum_{j=l_t}^{u_t} j z_{jt}, \quad \forall t \quad (21)$$

$$x_t, I_t \geq 0 \quad \forall t \quad (22)$$

$$y_t \in \{0, 1\} \quad \forall t \quad (23)$$

$$z_{jt} \in \{0, 1\} \quad \forall t \forall j \in d_t(min), \dots, d_t(max) \quad (24)$$

2.2.2 The aggregate stochastic formulation

$$\min \sum_{t=1}^T f_t y_t + \sum_{t=1}^T h_t \max \left(\left(\sum_{t'=1}^t x_{t'} - Dc_t \right), 0 \right) \quad (25)$$

$$x_t \leq C y_t \quad \forall t \in 1, \dots, T \quad (26)$$

$$\Pr \left(\sum_{t'=1}^t x_{t'} \geq Dc_t; \forall t \in 1, \dots, T \right) \geq 1 - \alpha \quad (27)$$

$$x_t \geq 0 \quad \forall t \in 1, \dots, T \quad (28)$$

$$y_t \in \{0, 1\} \quad \forall t \in 1, \dots, T \quad (29)$$

A Linearization of SM1

$$\text{Define the set } Z_\alpha = \{z \in [0, 1]^T | \Pr(d \leq z) \geq 1 - \alpha\} \quad (30)$$

where $d = (d_1, \dots, d_T)$

As d is the vector of independent random variables

$$\Pr(d \leq z) = \Pi_t(\Pr(d_t \leq z_t)) \quad (31)$$

Equation (13) can be rewritten as follows:

$$I_{t-1} + x_t - I_t \geq z_t; \quad \forall t \in 1, \dots, T \quad (32)$$

$$\Pi_t(\Pr[d_t \leq z_t]) \geq 1 - \alpha \quad (33)$$

In order to linearize equation (33) first we apply log and then we introduce the binary variables z_{jt} as follows:

$$\sum_{j=l_t}^{u_t} z_{jt} = 1, \forall t \quad (34)$$

$$z_t = \sum_{j=l_t}^{u_t} j z_{jt} \quad (35)$$

$$\sum_t \log(F_t(z_t)) \geq \log(1 - \alpha) \quad (36)$$

$$\sum_t \log(F_t(\sum_{j=l_t}^{u_t} j z_{jt})) \geq \log(1 - \alpha)$$

Finally we can linearize equation (36) as follows:

$$\sum_t \sum_{j=l_t}^{u_t} z_{jt} \log(F_t(j)) \geq \log(1 - \alpha) \quad (37)$$

B Linearization of SM2

The objective function (25) and the constraint (27) are random variables.

References