

CHANCE CONSTRAINED PROGRAMMING (CCP) WITH INDEPENDENT OR DEPENDENT EXPONENTIAL INPUT COEFFICIENTS

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ABSTRACT

In this paper, we consider Chance constrained programming (CCP) technique when at least two of the LHS input coefficients are random and distributed as two-parameter exponential distribution- Since two-parameter exponential distribution is more applicable in most real life applications than the single-parameter exponential distribution.

Two approaches are introduced to transform CCP into deterministic: (i) The first approach proposed under the assumption of independence between exponential variables and (ii) the second approach assumes that random input coefficients are dependent with correlation coefficient ρ .

The first approach of independence is an extension of Biswal's approach to deal with two-parameter exponential variables instead of single-parameter exponential variables. That is through two lemmas and a theorem for m independent input coefficients. The second approach of dependence uses Downton bivariate exponential distribution for reflecting the joint distribution of correlated input coefficients under two cases; the first introduced case assumes that dependent input coefficients have single-parameter exponential marginals and the second introduced case is an extension of Downton bivariate exponential distribution for case of two-parameter exponential random input coefficients. The deterministic equivalent of chance constraints are obtained through a theorem and a corollary for each case.

Finally; It was shown that the equivalent deterministic transformation for the extension of Downton exponential distribution for two-parameter exponential marginals is a generalization of the first approach for $m=2$ when the correlation coefficient is zero and the second approach for single-parameter exponential marginal when the second parameter is zero.

Keywords: *Bessel function, Bishwal approach, chance constrained programming, Downton bivariate exponential distribution, input coefficients, Non-linear programming, two-parameter exponential distribution.*

1. INTRODUCTION

In the nineteen forties, Mathematical Programming (MP) approaches underwent a rapid development, one of these approaches is Stochastic Programming approach where some or all of the model parameters are random variables, taking into account the probability distribution of the random parameters in the underlying problem [13]. Randomness may exist in the RHS parameter or some (or all) LHS input coefficients, or some (or all) objective function coefficients. In this paper we are concerned with the case when two of LHS input coefficients are random.

Consider the following linear programming model:

$$\text{Max. } z = \sum_{j=1}^m c_j x_j \quad (1)$$

S.t.;

$$\sum_{j=1}^{\tilde{m}} \tilde{a}_{ij} x_j + \sum_{j=\tilde{m}+1}^m a_{ij} x_j \leq b_i, \quad i = 1, 2, \dots, n; \quad x_j \geq 0 \quad (2)$$

$$j = 1, \dots, \tilde{m}, \tilde{m} + 1, \dots, m$$

we refer to the stochastic parameters as \tilde{a}_{ij} . CCP technique is one of the stochastic programming techniques developed by Charnes and Cooper [2;3;4] which offers powerful means of modeling stochastic decision problems with assumption that the stochastic constraints will hold with probability at least α , where α refers to the confidence level provided as an appropriate safety margin by the decision-maker and is called tolerance measure [11]. CCP aims to transform the stochastic model into a deterministic one, then solving the deterministic model using a suitable mathematical programming technique.

The exponential distribution is applicable for a wide class of economic, demographic and reliability models where the input coefficients and the resources have to be nonnegative, which require distributions with nonnegative range. As for exponentially distributed random input coefficients \tilde{a}_{ij} , constraint (2) is first manipulated in literature by Sengupta in 1972 assuming \tilde{a}_{ij} 's are independent two-parameter exponential random variables, he suggested the use of central χ^2 approximation. Then Biswal *et al.* in 1998 used different approach assuming \tilde{a}_{ij} 's are independent single-parameter exponential random variables; giving the exact distribution of the variable $\sum_{j=1}^m \tilde{a}_{ij}x_j$, from which the deterministic equivalent of the CC is derived. In this paper; we propose an approach to transform CCP into deterministic equivalent through introducing an extension of Biswal's approach by hypothesizing two-parameter exponential marginal instead of the single parameter exponential which doesn't suit in most real life applications due to having its mode at the origin.

Moreover; It is remarkable that the independence assumption was used by both approaches; Sengupta and Biswal approaches. However; in reality the assumption of independence in most situations is unrealistic, and parameters usually reflect dependent relationships among each other, where the assumption of independence is considered a special case of the dependence case. As for the bivariate exponential distribution, many different forms were presented in literature. Gumbel in 1960 presented the first type of bivariate exponential distribution, followed by Freund in 1961, then many other forms were presented after that [10]. However; no attempts were introduced to manipulate CCP with dependent exponential LHS parameters. In this paper; based on Downton's Bivariate exponential distribution introduced by Downton in 1970, we introduce an approach for transforming CCP into deterministic with bivariate dependent exponential LHS input coefficients. Besides; we introduce an extension of Downton bivariate exponential distribution assuming two-parameter exponential marginal, and of course the deterministic equivalent of CC is obtained

Throughout this paper; we are concerned with individual chance constraints taking one of the following forms:

$$P(\sum_{j=1}^m \tilde{a}_{ij}x_j \leq b_i) \geq \alpha_i; \quad i = 1, 2, \dots, n'; j = 1, \dots, m \quad (3)$$

$$P(\sum_{j=1}^{\tilde{m}} \tilde{a}_{ij}x_j + \sum_{j=\tilde{m}+1}^m a_{ij}x_j \leq b_i) \geq \alpha_i, \quad i = 1, 2, \dots, n; \\ j = 1, \dots, \tilde{m}, \tilde{m} + 1, \dots, m \quad (4)$$

where for $i = 1, 2, \dots, n'$; it is assumed that all LHS parameters \tilde{a}_{ij} of the i^{th} constraint are random variables, and for $i = (n' + 1), \dots, n$ only some of the LHS parameters $\tilde{a}_{ij}; j = 1, \dots, m'$ are random variables and the remaining LHS parameters $a_{ij}; j = m' + 1, \dots, m$ are deterministic.

The following sections are organized as follows; section 2 illustrates the proposed approach for dealing with CCP when some or all of LHS input coefficients are independent random variables distributed with two-parameter exponential distribution. Section 3 explains the proposed approach for dealing with CCP under the assumption that only two of the LHS input coefficients are random variables and distributed as bivariate Downton exponential distribution with correlation coefficient ρ . In section 4 we introduce an extension of the Downton bivariate exponential distribution to deal with two-parameter exponential random variables. Section 5 illustrate some numerical examples, and finally the summary and conclusions are provided.

2. APPROACH 1: CCP WITH INDEPENDENT INPUT COEFFICIENTS

As mentioned before Biswal *et al.* in 1998 considered constraint (3) assuming that \tilde{a}_{ij} 's are independent single-parameter exponential random variables; However; the single-parameter exponential distribution doesn't suit in most real life applications due to having its mode at the origin; therefore in this section we introduce an extension of Biswal's approach for two-parameter exponential random parameters, which overcome the previous drawback and is considered a generalization of Biswal's approach.

Recall constraint (3) and assume that \tilde{a}_{ij} 's are independently two-parameter exponentially distributed, with Pdf defined as;

$$f(\tilde{a}_{ij}) = \lambda_{ij} \exp\{-\lambda_{ij}(\tilde{a}_{ij} - \gamma_{ij})\} \quad ; \lambda_{ij} > 0; 0 \leq \gamma_{ij} \leq \tilde{a}_{ij} \quad (5)$$

Where γ_{ij} is the location parameter, λ_{ij} is the scale parameter, and with mean and variance:

$$E(\tilde{a}_{ij}) = \frac{1}{\lambda_{ij}} + \gamma_{ij}, \quad V(\tilde{a}_{ij}) = \left(\frac{1}{\lambda_{ij}}\right)^2 \quad (6)$$

By using the same approach of Biswal *et al.*, now we introduce an extension of Biswal *et al.* approach to deal with two-parameter exponential random variates in the LHS of constraints (3) or (4) through the following lemmas.

Lemma (2.1): let $\tilde{y}_i = \sum_{j=1}^2 \tilde{a}_{ij}x_j$; where \tilde{a}_{ij} ; $j = 1,2$ are independent exponential random variables with two parameters $(\lambda_{ij}; \gamma_{ij})$ and with known means $(\frac{1}{\lambda_{ij}} + \gamma_{ij})$ and variances $(\frac{1}{\lambda_{ij}})^2$; $\lambda_{ij} > 0, 0 \leq \gamma_{ij} \leq \tilde{a}_{ij}$, then for some scalars $x_j; j = 1,2$ the probability density function of the random variable \tilde{y}_i is given by:

$$g(\tilde{y}_i) = \exp\{\sum_{j=1}^2 \lambda_{ij}\gamma_{ij}\} \left(\frac{\lambda_{i1}\lambda_{i2}}{(x_1\lambda_{i2}-x_2\lambda_{i1})} \exp\left\{-\frac{\lambda_{i1}}{x_1}\tilde{y}_i - \left(\frac{x_1\lambda_{i2}-x_2\lambda_{i1}}{x_1}\right)\gamma_{i2}\right\} + \frac{\lambda_{i1}\lambda_{i2}}{(x_2\lambda_{i1}-x_1\lambda_{i2})} \exp\left\{-\frac{\lambda_{i2}}{x_2}\tilde{y}_i - \left(\frac{x_2\lambda_{i1}-x_1\lambda_{i2}}{x_2}\right)\gamma_{i1}\right\} \right); \tilde{y}_i \geq \gamma_{i1}x_{i1} + \gamma_{i2}x_{i2} \tag{7}$$

Proof: Let the i^{th} probabilistic constraint be

$$P(\tilde{a}_{i1}x_1 + \tilde{a}_{i2}x_2 \leq b_i) > \alpha_i \tag{8}$$

then the cumulative density function (c.d.f) of the random variable $\tilde{y}_i = \sum_{j=1}^2 \tilde{a}_{ij}x_j$ can be computed as:

$$G(\tilde{y}_i) = \int_{\tilde{a}_{i2}=\gamma_{i2}}^{\frac{\tilde{y}_i-\gamma_{i1}x_1}{x_2}} \int_{\tilde{a}_{i1}=\gamma_{i1}}^{\frac{\tilde{y}_i-\tilde{a}_{i2}x_2}{x_1}} \lambda_{i1}\lambda_{i2} \exp\{-\lambda_{i1}\tilde{a}_{i1} - \lambda_{i2}\tilde{a}_{i2} + \sum_{j=1}^2 \lambda_{ij}\gamma_{ij}\} d\tilde{a}_{i1} d\tilde{a}_{i2}$$

$$= \exp\{\sum_{j=1}^2 \lambda_{ij}\gamma_{ij}\} \left(\exp\{-\sum_{j=1}^2 \lambda_{ij}\gamma_{ij}\} - \frac{x_1\lambda_{i2}}{(x_1\lambda_{i2}-x_2\lambda_{i1})} \exp\left\{-\frac{\lambda_{i1}}{x_1}\tilde{y}_i - \left(\frac{x_1\lambda_{i2}-x_2\lambda_{i1}}{x_1}\right)\gamma_{i2}\right\} + \frac{x_2\lambda_{i1}}{(x_1\lambda_{i2}-x_2\lambda_{i1})} \exp\left\{-\frac{\lambda_{i2}}{x_2}\tilde{y}_i - \left(\frac{x_2\lambda_{i1}-x_1\lambda_{i2}}{x_2}\right)\gamma_{i1}\right\} \right) \tag{9}$$

By differentiation with respect to \tilde{y}_i ; we obtain the pdf of \tilde{y}_i in (7)

Lemma (2.2): let $\tilde{y}_i = \sum_{j=1}^3 \tilde{a}_{ij}x_j$; where \tilde{a}_{ij} ; $j = 1,2,3$ are independent exponential random variables with two parameters $(\lambda_{ij}; \gamma_{ij})$ and with known means $(\frac{1}{\lambda_{ij}} + \gamma_{ij})$ and variances $(\frac{1}{\lambda_{ij}})^2$; $\lambda_{ij} > 0, 0 \leq \gamma_{ij} \leq \tilde{a}_{ij}$, then for some scalars $x_j; j = 1,2,3$ the probability density function of the random variable \tilde{y}_i is given by:

$$g(\tilde{y}_i) = \exp\{\sum_{j=1}^3 \lambda_{ij}\gamma_{ij}\} \left(\frac{\lambda_{i1}\lambda_{i2}\lambda_{i3}}{(x_1\lambda_{i2}-x_2\lambda_{i1})(x_1\lambda_{i3}-x_3\lambda_{i1})} \exp\left\{-\frac{\lambda_{i1}}{x_1}\tilde{y}_i - \sum_{j=2}^3 \left(\frac{x_1\lambda_{ij}-x_j\lambda_{i1}}{x_1}\right)\gamma_{ij}\right\} + \frac{\lambda_{i1}\lambda_{i2}\lambda_{i3}}{(x_2\lambda_{i1}-x_1\lambda_{i2})(x_2\lambda_{i3}-x_3\lambda_{i2})} \exp\left\{-\frac{\lambda_{i2}}{x_2}\tilde{y}_i - \sum_{j=1}^3 \left(\frac{x_2\lambda_{ij}-x_j\lambda_{i2}}{x_2}\right)\gamma_{ij}\right\} + \frac{\lambda_{i1}\lambda_{i2}\lambda_{i3}}{(x_3\lambda_{i1}-x_1\lambda_{i3})(x_3\lambda_{i2}-x_2\lambda_{i3})} \exp\left\{-\frac{\lambda_{i3}}{x_3}\tilde{y}_i - \sum_{j=1}^2 \left(\frac{x_3\lambda_{ij}-x_j\lambda_{i3}}{x_3}\right)\gamma_{ij}\right\} \right); \tilde{y}_i \geq \sum_{j=1}^3 \gamma_{ij}x_j \tag{10}$$

Proof: similar to proof of lemma (2.1).

The following theorem provides the general form of the density function of the random variable $\tilde{y}_i = \sum_{j=1}^m \tilde{a}_{ij}x_j$; where \tilde{a}_{ij} 's are independent exponential random variables with two parameters. And the deterministic transformation of constraint (3).

Theorem (2.1): let the i^{th} constraint be of the form of (3) .and let $\tilde{y}_i = \sum_{j=1}^m \tilde{a}_{ij}x_j$ where \tilde{a}_{ij} ; $j = 1, \dots, m$, are independent two-parameter exponential random variables with $(\lambda_{ij}; \gamma_{ij})$ and with known means $(\frac{1}{\lambda_{ij}} + \gamma_{ij})$ and variances $(\frac{1}{\lambda_{ij}})^2$; $\lambda_{ij} > 0, 0 \leq \gamma_{ij} \leq \tilde{a}_{ij}$, Then:

i) The probability density function of the random variable \tilde{y}_i for some scalars $x_j; j = 1; \dots; m$ is given by $g(\tilde{y}_i)$

$$g(\tilde{y}_i) = \left(\prod_{j=1}^m \lambda_{ij} \right) \exp\left\{ \sum_{j=1}^m \lambda_{ij} \gamma_{ij} \right\} \left[\frac{x_j^{m-2} \exp\left\{ -\frac{\lambda_{ij} \tilde{y}_i}{x_j} - \sum_{\substack{l=1 \\ l \neq j}}^m \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\}}{\prod_{\substack{l=1 \\ l \neq j}}^m (x_j \lambda_{il} - x_l \lambda_{ij})} \right];$$

$$\tilde{y}_i \geq \sum_{j=1}^m \gamma_{ij} x_{ij} \tag{11}$$

ii) The deterministic equivalent of constraint (3) is:

$$- \sum_{j=1}^m \frac{x_j^{m-1} \exp\left\{ -\frac{\lambda_{ij} b_i}{x_j} - \sum_{\substack{l=1 \\ l \neq j}}^m \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\}}{\lambda_{ik} \prod_{\substack{l=1 \\ l \neq k}}^m (x_k \lambda_{il} - x_l \lambda_{ik})} \geq \frac{\alpha_i}{\left(\prod_{j=1}^m \lambda_{ij} \right) \exp\left\{ \sum_{j=1}^m \lambda_{ij} \gamma_{ij} \right\}}; i = 1, \dots, n' \tag{12}$$

Proof: the proof of the first part is based on mathematical induction, therefore the proof consists of three steps.

1) At first we want to prove the relation (11) is true for m=1 and m=2:

• For m=1:

$$\text{LHS} = g(\tilde{y}_i = \tilde{a}_{i1} x_1) = \frac{\lambda_{i1}}{x_1} \exp\left\{ -\frac{\lambda_{i1} \tilde{y}_i}{x_1} + \lambda_{i1} \gamma_{i1} \right\} = \text{RHS}$$

Therefore the relation is true for m = 1

• For m=2:

$$\text{RHS} = \lambda_{i1} \lambda_{i2} e^{\sum_{j=1}^2 \lambda_{ij} \gamma_{ij}} \left(\frac{1}{(x_1 \lambda_{i2} - x_2 \lambda_{i1})} \exp\left\{ -\frac{\lambda_{i1} \tilde{y}_i}{x_1} - \left(\frac{x_1 \lambda_{i2} - x_2 \lambda_{i1}}{x_1} \right) \gamma_{i2} \right\} + \frac{1}{(x_2 \lambda_{i1} - x_1 \lambda_{i2})} \exp\left\{ -\frac{\lambda_{i2} \tilde{y}_i}{x_2} - \left(\frac{x_2 \lambda_{i1} - x_1 \lambda_{i2}}{x_2} \right) \gamma_{i1} \right\} \right)$$

which equals the LHS for m=2 by lemma (2.1)

2) Assume that the relation (11) is true for m = r ; Then the Pdf of $\tilde{y}_i = \sum_{j=1}^r \tilde{a}_{ij} x_j$ is:

$$g(\tilde{y}_i) = C_r \left[\frac{x_j^{r-2} \exp\left\{ -\frac{\lambda_{ij} \tilde{y}_i}{x_j} - \sum_{\substack{l=1 \\ l \neq j}}^r \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\}}{\prod_{\substack{l=1 \\ l \neq j}}^r (x_j \lambda_{il} - x_l \lambda_{ij})} \right]; \tilde{y}_i \geq \sum_{j=1}^r \gamma_{ij} x_j \tag{13}$$

where $C_r = \left(\prod_{j=1}^r \lambda_{ij} \right) \exp\left\{ \sum_{j=1}^r \lambda_{ij} \gamma_{ij} \right\}$

3) Now; we need to proof that the relation holds for m = r + 1

Let $\tilde{y}_i = \sum_{j=1}^{r+1} \tilde{a}_{ij} x_j = \tilde{a} + \tilde{a}_{i(r+1)} x_{(r+1)}$ where the pdf of $\tilde{a} = \sum_{j=1}^r \tilde{a}_{ij} x_j$ and $\tilde{a}_{i(r+1)}$ are given by $g(\tilde{a})$ and $f(\tilde{a}_{i(r+1)})$ respectively:

$$g(\tilde{a}) = C_r \left[\frac{x_j^{r-2} \exp\left\{ -\frac{\lambda_{ij} \tilde{a}}{x_j} - \sum_{\substack{l=1 \\ l \neq j}}^r \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\}}{\prod_{\substack{l=1 \\ l \neq j}}^r (x_j \lambda_{il} - x_l \lambda_{ij})} \right]; \tilde{a} \geq \sum_{j=1}^r \gamma_{ij} x_j \tag{14}$$

$$f(\tilde{a}_{i(r+1)}) = \lambda_{i(r+1)} e^{-\lambda_{i(r+1)}(\tilde{a}_{i(r+1)} - \gamma_{i(r+1)})}; \tilde{a}_{i(r+1)} \geq \gamma_{i(r+1)} \tag{15}$$

The CDF of $\tilde{y}_i = \tilde{a} + \tilde{a}_{i(r+1)} x_{(r+1)}$ is given by

$$G(\tilde{y}_i) = \int_{\tilde{a}_{i(r+1)} = \gamma_{i(r+1)}}^{\frac{\tilde{y}_i - \sum_{j=1}^r \gamma_{ij} x_j}{x_{(r+1)}}} \int_{\tilde{a} = \sum_{j=1}^r \gamma_{ij} x_j}^{\tilde{y}_i - \tilde{a}_{i(r+1)} x_{(r+1)}} g(\tilde{a}) f(\tilde{a}_{i(r+1)}) d\tilde{a} d\tilde{a}_{i(r+1)} \tag{16}$$

$$= C_{r+1} \cdot \int_{\tilde{a}_{i(r+1)} = \gamma_{i(r+1)}}^{\frac{\tilde{y}_i - \sum_{j=1}^r \gamma_{ij} x_j}{x_{(r+1)}}} \int_{\tilde{a} = \sum_{j=1}^r \gamma_{ij} x_j}^{\tilde{y}_i - \tilde{a}_{i(r+1)} x_{(r+1)}} \left[\frac{x_j^{r-2} \exp\left\{ -\lambda_{i(r+1)} \tilde{a}_{i(r+1)} \right\}}{\prod_{\substack{l=1 \\ l \neq j}}^r (x_j \lambda_{il} - x_l \lambda_{ij})} \exp\left\{ -\frac{\lambda_{ij} \tilde{a}}{x_j} - \sum_{\substack{l=1 \\ l \neq j}}^r \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\} \right] d\tilde{a} d\tilde{a}_{i(r+1)} \tag{17}$$

Where $C_{r+1} = \left(\prod_{j=1}^{r+1} \lambda_{ij} \right) \exp\left\{ \sum_{j=1}^{r+1} \lambda_{ij} \gamma_{ij} \right\}$

$$= C_{r+1} \int_{\tilde{a}_i(r+1)=\gamma_i(r+1)}^{\frac{(\tilde{y}_i - \sum_{j=1}^r \gamma_{ij} x_j)}{x^{(r+1)}}} \frac{x_j^{r-1}}{\lambda_{ij} \prod_{l=1}^r (x_j \lambda_{il} - x_l \lambda_{ij})} \cdot \left[\exp \left\{ -\lambda_{i(r+1)} \tilde{a}_{i(r+1)} - \frac{\lambda_{ij}}{x_j} \sum_{j=1}^r \gamma_{ij} x_j - \sum_{l=1}^r \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\} - \exp \left\{ -\left(\frac{x_j \lambda_{i(r+1)} - x^{(r+1)} \lambda_{ij}}{x_j} \right) \tilde{a}_{i(r+1)} - \frac{\lambda_{ij}}{x_j} \tilde{y}_i - \sum_{l=1}^r \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\} \right] d\tilde{a}_{i(r+1)} \quad (18)$$

$$= C_{r+1} \sum_{j=1}^r \left[\frac{x_j^{r-1}}{\lambda_{ij} \lambda_{i(r+1)} \prod_{l=1}^r (x_j \lambda_{il} - x_l \lambda_{ij})} \left(\exp \left\{ -\lambda_{i(r+1)} \gamma_{i(r+1)} - \frac{\lambda_{ij}}{x_j} \sum_{j=1}^r \gamma_{ij} x_j - \sum_{l=1}^r \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\} - \exp \left\{ -\frac{\lambda_{i(r+1)}}{x^{(r+1)}} \tilde{y}_i - \sum_{l=1}^{r+1} \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\} \right) - \frac{x_j^r}{\lambda_{ij} \prod_{l=1}^{r+1} (x_j \lambda_{il} - x_l \lambda_{ij})} \left(\exp \left\{ -\frac{\lambda_{ij}}{x_j} \tilde{y}_i - \sum_{l=1}^{r+1} \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\} - \exp \left\{ -\frac{\lambda_{i(r+1)}}{x^{(r+1)}} \tilde{y}_i - \sum_{l=1}^{r+1} \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\} \right) \right] \quad (19)$$

The Pdf of \tilde{y}_i can be obtained by differentiating $G(\tilde{y}_i)$ with respect to \tilde{y}_i :

$$g(\tilde{y}_i) = C_{r+1} \left[\frac{x_j^{(r+1)-2} \exp \left\{ -\frac{\lambda_{ij} \tilde{y}_i}{x_j} - \sum_{l=1}^{r+1} \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\}}{\prod_{l=1}^{r+1} (x_j \lambda_{il} - x_l \lambda_{ij})} \right]; \tilde{y}_i \geq \sum_{j=1}^{r+1} \gamma_{ij} x_j \quad (20)$$

Which is the same as the RHS of (11) for $m = r + 1$. This completes the proof of the first part.

The second part of theorem (2.1) is the transformation of constraint (3) into deterministic through integrating the Pdf of \tilde{y}_i as stated below

$$\int_{\sum_{j=1}^m \gamma_{ij} x_j}^{b_i} g(y_i) dy_i \geq \alpha_i \quad ; \quad i = 1, \dots, n' \quad (21)$$

$$- \sum_{j=1}^m \frac{x_j^{m-1} \exp \left\{ -\frac{\lambda_{ij} b_i}{x_j} - \sum_{l=1}^m \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\}}{\lambda_{ij} \prod_{l=1}^m (x_j \lambda_{il} - x_l \lambda_{ij})} \geq \frac{\alpha_i}{(\prod_{j=1}^m \lambda_{ij}) \exp \{ \sum_{j=1}^m \lambda_{ij} \gamma_{ij} \}}; i = 1, \dots, n' \quad (22)$$

Now; Consider constraint (4), the deterministic equivalent can be obtained by integrating the p.d.f. of \tilde{y}_i as stated by the following corollary.

Corollary (2.1): Let the i^{th} CC be of the form of (4), and let $\tilde{y}_i = \sum_{j=1}^m \tilde{a}_{ij} x_j$ where $\tilde{a}_{ij}; j = 1, \dots, m$, are independent two-parameter exponential random variables with $(\lambda_{ij}; \gamma_{ij})$ and with known means $\left(\frac{1}{\lambda_{ij}} + \gamma_{ij} \right); \lambda_{ij} > 0, 0 \leq \gamma_{ij} \leq \tilde{a}_{ij}$, then for some scalars $x_j; j = 1; \dots; m$, the deterministic equivalent of the CC (4) is:

$$- \sum_{j=1}^m \frac{x_j^{m-1} \exp \left\{ -\frac{\lambda_{ij} (b_i - \sum_{j=m+1}^m a_{ij} x_j)}{x_j} - \sum_{l=1}^m \left(\frac{x_j \lambda_{il} - x_l \lambda_{ij}}{x_j} \right) \gamma_{il} \right\}}{\lambda_{ij} \prod_{l=1}^m (x_j \lambda_{il} - x_l \lambda_{ij})} \geq \frac{\alpha_i}{(\prod_{j=1}^m \lambda_{ij}) \exp \{ \sum_{j=1}^m \lambda_{ij} \gamma_{ij} \}}; i = n' + 1, \dots, n \quad (23)$$

Proof: based on the The Pdf of \tilde{y}_i which is obtained in theorem (2.1), then the deterministic equivalent of (4) could be obtained by integrating the p.d.f. of \tilde{y}_i as below

$$\int_{\sum_{j=1}^m \gamma_{ij} x_j}^{b_i - \sum_{j=m+1}^m a_{ij} x_j} g(y_i) dy_i \geq \alpha_i \quad ; \quad i = n' + 1, \dots, n \quad (24)$$

$$-\sum_{j=1}^m \frac{x_j^{m-1} \exp\left\{-\frac{\lambda_{ij}(b_i - \sum_{l=j}^m a_{il} x_l)}{x_j} - \sum_{l=1, l \neq j}^m \left(\frac{x_l \lambda_{il} - x_l \lambda_{ij}}{x_j}\right) \gamma_{il}\right\}}{\lambda_{ij} \prod_{l=1, l \neq j}^m (x_l \lambda_{il} - x_l \lambda_{ij})} \geq \frac{\alpha_i}{\left(\prod_{j=1}^m \lambda_{ij}\right) \exp\left\{\sum_{j=1}^m \lambda_{ij} \gamma_{ij}\right\}} ;$$

$$i = n' + 1, \dots, n \tag{25}$$

Special cases

1) Consider the special case where $m = 2$ that is :

$$P(\tilde{a}_{i1}x_1 + \tilde{a}_{i2}x_2 \leq b_i) \geq \alpha_i \tag{26}$$

Then; the deterministic transformation of the chance constraint (26) could be obtained by (22) as:

$$-\left[\frac{x_1 \exp\left\{\frac{-(x_1 \lambda_{i2} - x_2 \lambda_{i1}) \gamma_{i2} - \lambda_{i1} b_i}{x_1}\right\}}{\lambda_{i1}(x_1 \lambda_{i2} - x_2 \lambda_{i1})} + \frac{x_2 \exp\left\{\frac{-(x_2 \lambda_{i1} - x_1 \lambda_{i2}) \gamma_{i1} - \lambda_{i2} b_i}{x_2}\right\}}{\lambda_{i2}(x_2 \lambda_{i1} - x_1 \lambda_{i2})} \right] \geq \frac{\alpha_i}{\lambda_{i1} \lambda_{i2} \exp\left\{\sum_{j=1}^2 \lambda_{ij} \gamma_{ij}\right\}} ; i = 1, \dots, n \tag{27}$$

2) Consider the special case of only two input coefficients are random and the remaining coefficients are deterministic; that is :

$$P(\tilde{a}_{i1}x_1 + \tilde{a}_{i2}x_2 + \sum_{j=3}^m a_{ij}x_j \leq b_i) \geq \alpha_i \tag{28}$$

Then the deterministic equivalent of constraint (28) is given by (23) as:

$$-\left[\frac{x_1 \exp\left\{\frac{-(x_1 \lambda_{i2} - x_2 \lambda_{i1}) \gamma_{i2} - \lambda_{i1}(b_i - \sum_{j=3}^m a_{ij}x_j)}{x_1}\right\}}{\lambda_{i1}(x_1 \lambda_{i2} - x_2 \lambda_{i1})} + \frac{x_2 \exp\left\{\frac{-(x_2 \lambda_{i1} - x_1 \lambda_{i2}) \gamma_{i1} - \lambda_{i2}(b_i - \sum_{j=3}^m a_{ij}x_j)}{x_2}\right\}}{\lambda_{i2}(x_2 \lambda_{i1} - x_1 \lambda_{i2})} \right] \geq \frac{\alpha_i}{\lambda_{i1} \lambda_{i2} \exp\left\{\sum_{j=1}^2 \lambda_{ij} \gamma_{ij}\right\}} ; i = 1, \dots, n \tag{29}$$

3) Consider the case when $\gamma_{ij} = 0, j = 1, \dots, m$; then the PDF of $\tilde{y}_i = \sum_{j=1}^m \tilde{a}_{ij}x_j$ obtained in theorem (2.1) is reduced to the corresponding pdf of single-parameter exponential variates obtained by Biswal. This indicates that the proposed extension introduced in this section for two-parameter exponential variates is a generalization of Biswal's approach.

3. APPROACH 2: FOR DEPENDENT SINGLE-PARAMETER EXPONENTIAL INPUT COEFFICIENTS

Consider again constraints (3) and (4), Our objective in this section is to find the deterministic equivalent of the probabilistic constraints (3) and (4) when $\tilde{a}_{ij}; j = 1, 2$ are dependent random parameters and distributed according to Downton's Bivariate exponential distribution – introduced by Downton in 1970. The approximated Downton bivariate exponential joint density function $f(\tilde{a}_1, \tilde{a}_2)$ is [9]:

$$f(\tilde{a}_1, \tilde{a}_2) = \frac{\lambda_1 \lambda_2}{(1-\rho)^2} \exp\left\{-\frac{\lambda_1 \tilde{a}_1 + \lambda_2 \tilde{a}_2}{1-\rho}\right\}; \tilde{a}_1, \tilde{a}_2 > 0; \lambda_1, \lambda_2 > 0; 0 \leq \rho \leq 1 \tag{30}$$

where ρ is the correlation between \tilde{a}_1, \tilde{a}_2

Theorem (3.1): Let the i^{th} CC be of the form of (3), and let $\tilde{y}_i = \tilde{a}_{i1}x_1 + \tilde{a}_{i2}x_2 (a_{i1}, a_{i2})^T$ are approximate Downton bivariate exponential random variables with joint density function $f(\tilde{a}_{i1}, \tilde{a}_{i2})$ defined in (30), ..Then;

i) \tilde{y}_i is distributed with Probability density function $g(\tilde{y}_i)$:

$$g(\tilde{y}_i) = \frac{\lambda_{i1} \lambda_{i2}}{(1-\rho_i)(\lambda_{i2}x_1 - \lambda_{i1}x_2)} \exp\left\{-\frac{\lambda_{i1}}{(1-\rho_i)x_1}(\tilde{y}_i)\right\} + \frac{\lambda_{i1} \lambda_{i2}}{(1-\rho_i)(\lambda_{i1}x_2 - \lambda_{i2}x_1)} \exp\left\{-\frac{\lambda_{i2}}{(1-\rho_i)x_2}(\tilde{y}_i)\right\} \tag{31}$$

ii) the deterministic equivalent of the CC (3) is:

$$\frac{\lambda_{i1}x_2}{(\lambda_{i1}x_2 - \lambda_{i2}x_1)} \exp\left\{-\frac{\lambda_{i2}}{(1-\rho_i)}\left(\frac{b_i}{x_2}\right)\right\} + \frac{\lambda_{i2}x_1}{(\lambda_{i2}x_1 - \lambda_{i1}x_2)} \exp\left\{-\frac{\lambda_{i1}}{(1-\rho_i)}\left(\frac{b_i}{x_1}\right)\right\} \leq 1 - \alpha_i \tag{32}$$

Proof: The proof is straightforward, in the first part we use the method of distribution functions through Firstly, deriving the distribution function of \tilde{y} by double integrating $f(\tilde{a}_{i1}, \tilde{a}_{i2})$ as follows:

$$G(\tilde{y}_i) = \int_{\tilde{a}_{i2}=0}^{\tilde{y}_i} \int_{\tilde{a}_{i1}=0}^{\tilde{y}_i - \tilde{a}_{i2}x_2} \frac{\lambda_1 \lambda_2}{(1-\rho_i)^2} \exp\left\{-\frac{\lambda_1 \tilde{a}_{i1} + \lambda_2 \tilde{a}_{i2}}{(1-\rho_i)}\right\} d\tilde{a}_{i1} d\tilde{a}_{i2} \quad (33)$$

Then Differentiating $G(\tilde{y})$ with respect to \tilde{y} to obtain the P.d.f. of \tilde{y} as $g(\tilde{y}_i)$. For second part; the deterministic equivalent of constraint (3) could be found by integrating $g(\tilde{y}_i)$ as follows:

$$\int_0^{b_i} g(\tilde{y}_i) d\tilde{y}_i \geq \alpha_i \quad ; \quad i = 1, \dots, n \quad (34)$$

Corollary (3.1): Let the i^{th} CC be of the form of (4), and let $(a_{i1}, a_{i2})^T$ are approximate Downton bivariate exponential random variables with joint density function $f(\tilde{a}_{i1}, \tilde{a}_{i2})$ defined in (30), Then the deterministic equivalent of the CC is:

$$\frac{\lambda_{i1}x_2}{(\lambda_{i1}x_2 - \lambda_{i2}x_1)} \exp\left\{-\frac{\lambda_{i2}}{(1-\rho_i)}\left(\frac{b_i - \sum_{j=3}^m a_{ij}x_j}{x_2}\right)\right\} + \frac{\lambda_{i2}x_1}{(\lambda_{i2}x_1 - \lambda_{i1}x_2)} \exp\left\{-\frac{\lambda_{i1}}{(1-\rho_i)}\left(\frac{b_i - \sum_{j=3}^m a_{ij}x_j}{x_1}\right)\right\} \leq 1 - \alpha_i \quad (35)$$

4. APPROACH 2: FOR DEPENDENT TWO-PARAMETER EXPONENTIAL INPUT COEFFICIENTS

In this section we will propose an extension of the approximated Downton bivariate exponential distribution which is based on two-parameter exponential marginal, where we assume the marginal pdf of \tilde{a}_{ij} is

$$f(\tilde{a}_{ij}) = \lambda_{ij} \exp\{-\lambda_{ij}(\tilde{a}_{ij} - \gamma_{ij})\} \quad ; \quad \lambda_{ij} > 0; \quad 0 \leq \gamma_{ij} \leq \tilde{a}_{ij} \quad (36)$$

The suggested extension of the approximated Pdf of Downton bivariate exponential distribution in (30) for the case of two-parameter exponential marginals could be expressed as (37):

$$f(\tilde{a}_{i1}, \tilde{a}_{i2}) = \frac{\lambda_{i1}\lambda_{i2}}{(1-\rho_i)^2} \exp\left\{-\frac{\lambda_{i1}(\tilde{a}_{i1} - \gamma_{i1}) + \lambda_{i2}(\tilde{a}_{i2} - \gamma_{i2})}{1-\rho_i}\right\}; \lambda_{ij} > 0, 0 \leq \gamma_{ij} \leq \tilde{a}_j, \quad (37)$$

$$0 \leq \rho_i \leq 1; j = 1, 2$$

Similar to previous derivations in case of Downton bivariate single-parameter exponential distribution in sections 3, we will derive the distribution of $\sum_{j=1}^2 \tilde{a}_{ij}x_j$, Assuming that $\tilde{a}_{i1}, \tilde{a}_{i2}$ are distributed as Downton bivariate two-parameter exponential random variates with Pdf defined in (37). And transform the CC (3) and (4) into deterministic.

Theorem (4.1): Let the i^{th} CC be of the form of (3) with $j = 1, 2$, and let $\tilde{y}_i = \sum_{j=1}^2 \tilde{a}_{ij}x_j$; where $(\tilde{a}_{i1}, \tilde{a}_{i2})^T$ are the approximated Downton bivariate two-parameter exponential random variables with approximated joint density function $f(\tilde{a}_{i1}, \tilde{a}_{i2})$ defined in (37), Then:

i) \tilde{y}_i is distributed with Probability density function $g(\tilde{y}_i)$:

$$g(\tilde{y}_i) = \frac{\lambda_{i1}\lambda_{i2}}{(1-\rho_i)} \exp\left\{\frac{\sum_{j=1}^2 \lambda_{ij}\gamma_{ij}}{(1-\rho_i)}\right\} \left(-\frac{1}{x_1\lambda_{i2} - x_2\lambda_{i1}} \exp\left\{-\frac{\lambda_{i2}}{(1-\rho_i)x_2}\tilde{y}_i - \left(\frac{x_2\lambda_{i1} - x_1\lambda_{i2}}{(1-\rho_i)x_2}\right)\gamma_{i1}\right\} + \right.$$

$$\left. \frac{1}{x_1\lambda_{i2} - x_2\lambda_{i1}} \exp\left\{-\frac{\lambda_{i1}}{(1-\rho_i)x_1}\tilde{y}_i - \left(\frac{x_1\lambda_{i2} - x_2\lambda_{i1}}{(1-\rho_i)x_1}\right)\gamma_{i2}\right\} \right); \tilde{y}_i \geq \gamma_{i1}x_1 + \gamma_{i2}x_2 \quad (38)$$

ii) the deterministic equivalent of the CC (3) is:

$$-\left[\frac{x_1 \exp\left\{\frac{-(x_1\lambda_{i2} - x_2\lambda_{i1})\gamma_{i2} - \lambda_{i1}b_i}{(1-\rho_i)x_1}\right\}}{\lambda_{i1}(x_1\lambda_{i2} - x_2\lambda_{i1})} + \frac{x_2 \exp\left\{\frac{-(x_2\lambda_{i1} - x_1\lambda_{i2})\gamma_{i1} - \lambda_{i2}b_i}{(1-\rho_i)x_2}\right\}}{\lambda_{i2}(x_2\lambda_{i1} - x_1\lambda_{i2})} \right] \geq \frac{\alpha_i}{\lambda_{i1}\lambda_{i2} \exp\left\{\frac{\sum_{j=1}^2 \lambda_{ij}\gamma_{ij}}{(1-\rho_i)}\right\}}; i = 1, \dots, n \quad (39)$$

Proof: the same idea of the proof of theorem (3.1). Firstly, we use the method of distribution functions to derive the distribution function of \tilde{y}_i by double Integrating $f(\tilde{a}_{i1}, \tilde{a}_{i2})$ as follows:

$$G(\tilde{y}_i) = \int_{\tilde{a}_{i2}=\gamma_{i2}}^{\frac{\tilde{y}_i-\gamma_{i1}x_1}{x_2}} \int_{\tilde{a}_{i1}=\gamma_{i1}}^{\frac{\tilde{y}_i-\tilde{a}_{i2}x_2}{x_1}} \frac{\lambda_{i1}\lambda_{i2}}{(1-\rho_i)^2} \exp\left\{\frac{\sum_{j=1}^2 \lambda_{ij}\gamma_{ij}}{(1-\rho_i)}\right\} \exp\left\{-\frac{\lambda_{i1}\tilde{a}_{i1}+\lambda_{i2}\tilde{a}_{i2}}{(1-\rho_i)}\right\} d\tilde{a}_{i1}d\tilde{a}_{i2} \quad (40)$$

Then, obtain the pdf $g(\tilde{y}_i)$ by differentiation with respect to \tilde{y}_i .

Secondly; a deterministic equivalent of constraint (3) could be found by integrating $g(\tilde{y}_i)$ as follows:

$$\int_{\gamma_{i1}x_1+\gamma_{i2}x_2}^{b_i} g(\tilde{y}_i)d\tilde{y}_i \geq \alpha_i \quad ; \quad i = 1, \dots, n \quad (41)$$

Corollary (4.1): Let the i^{th} CC be of the form of (4); with $j = 1,2$, and let $(\tilde{a}_{i1}, \tilde{a}_{i2})^T$ are approximate Downton bivariate two-parameter exponential random variables with joint density function $f(\tilde{a}_{i1}, \tilde{a}_{i2})$ defined in (37), Then the deterministic equivalent of the CC is:

$$-\left[\frac{x_1 \exp\left\{\frac{-(x_1\lambda_{i2}-x_2\lambda_{i1})\gamma_{i2}-\lambda_{i1}(b_i-\sum_{j=3}^m \tilde{a}_{ij}x_j)}{(1-\rho_i)x_1}\right\}}{\lambda_{i1}(x_1\lambda_{i2}-x_2\lambda_{i1})} + \frac{x_2 \exp\left\{\frac{-(x_2\lambda_{i1}-x_1\lambda_{i2})\gamma_{i1}-\lambda_{i2}(b_i-\sum_{j=3}^m \tilde{a}_{ij}x_j)}{(1-\rho_i)x_2}\right\}}{\lambda_2(x_2\lambda_{i1}-x_1\lambda_{i2})} \right] \geq \frac{\alpha_i}{\lambda_{i1}\lambda_{i2} \exp\left\{\frac{\sum_{j=1}^2 \lambda_{ij}\gamma_{ij}}{(1-\rho_i)}\right\}} \quad ; \quad i = 1, \dots, n' \quad (42)$$

Special cases:

- 1) As special case of (39) and (42), when $\rho_i = 0$; that is if independence is assumed between \tilde{a}_1 and \tilde{a}_2 , the deterministic constraint (39) and (42) which is based on approximate Downton bivariate two-parameter exponential distribution- will be reduced to the deterministic constraint (27) and (29); respectively which are proposed in section 2 based on the joint distribution of independent two-parameter exponential random parameters with exponential marginal. That is to say the deterministic equivalents (39) and (42) are the generalized deterministic equivalents of (27) and (29) with respect to correlation between parameters.
- 2) Also; setting $\gamma_{ij} = 0$; $j = 1,2$ in constraints (39) and (42) reduces them to the deterministic equivalents (32) and (35) respectively proposed in section 3 which are based on approximate bivariate Downton exponential with single-parameter. That is to say the deterministic equivalents (39) and (42) are the generalized deterministic equivalents of (32) and (35) with respect to number of parameters of exponential marginals.

5. NUMERICAL EXAMPLES

In this section we demonstrate the two proposed approaches in this paper through two examples. Both examples assumes LHS input coefficients are random with two-parameter exponential marginals.

Example (1): This example illustrates the deterministic transformation of probabilistic model assuming independence between the LHS parameters using approach 1. Consider the probabilistic programming model

$$Max Z = 5x_1 + 6x_2 \quad (43)$$

S.t.;

$$P(\tilde{a}_{11}x_1 + \tilde{a}_{12}x_2 \leq 10) \geq 0.95 \quad (44)$$

$$3x_1 + 6x_2 \leq 4 \quad (45)$$

$$x_1, x_2 \geq 0 \quad (46)$$

where \tilde{a}_{ij} ; $i = 1; j = 1,2$ are independent two-parameter exponential distribution with $\lambda_{11} = \frac{1}{5}$, $\lambda_{12} = \frac{1}{4}$, $\gamma_{11} = 1$, and $\gamma_{12} = 1$

Constraint (44) could be transformed into equivalent deterministic using (12) and model (43)- (46) becomes as follows:

$$\text{Max } Z = 5x_1 + 6x_2 \quad (47)$$

S.t.;

$$4x_2 \exp\left\{-\frac{0.2x_2 - 0.25x_1 + 2.5}{x_2}\right\} - 5x_1 \exp\left\{-\frac{0.25x_1 - 0.2x_2 + 2}{x_1}\right\} - 12.11493(0.25x_1 - 0.2x_2) \geq 0 \quad (48)$$

$$3x_1 + 6x_2 \leq 4 \quad (49)$$

$$x_1, x_2 \geq 0 \quad (50)$$

The deterministic equivalent model (47)- (50) is a non-linear programming model which could be solved using one of the non-linear programming techniques [9; 12].

Example 2: This example illustrates the deterministic transformation of probabilistic model assuming dependence between LHS parameters using approach (2).

Consider the probabilistic programming model (43)- (46)- Where $\tilde{a}_{ij}; i = 1; j = 1, 2$ are distributed as approximate Downton bivariate two-parameter exponential distribution with $\lambda_{11} = \frac{1}{5}$, $\lambda_{12} = \frac{1}{4}$, $\gamma_{11} = 1$, and $\gamma_{12} = 1$ and correlation $\rho_1 = 0.4$.

Constraint (44) could be transformed into deterministic using (39) and model (43)- (46) becomes as follows:

$$\text{Max } Z = 5x_1 + 6x_2 \quad (51)$$

S.t.;

$$4x_2 \exp\left\{-\frac{0.2x_2 - 0.25x_1 + 2.5}{0.6x_2}\right\} - 5x_1 \exp\left\{-\frac{0.25x_1 - 0.2x_2 + 2}{0.6x_1}\right\} - 8.97(0.25x_1 - 0.2x_2) \geq 0 \quad (52)$$

$$3x_1 + 6x_2 \leq 4 \quad (53)$$

$$x_1, x_2 \geq 0 \quad (54)$$

Again; the deterministic equivalent model (51)- (54) is a non-linear programming model which could be solved using one of the non-linear programming techniques [9; 12].

6. OVERALL CONCLUSIONS

In this paper, we proposed two approaches for transforming CCP models into deterministic; where the randomness exists in the LHS input coefficients.

The first approach assumes that the input coefficients are independent and distributed as two-parameter exponential distribution. The equivalent deterministic transformation of CC is introduced through lemma (2.1), lemma (2.2) and theorem (2.1) and corollary (2.1) for m input coefficients. It was shown that this approach is a generalization of Biswal approach for independent single-parameter exponential distribution.

The second approach assumes that the input coefficients are correlated with approximated single parameter Downton bivariate exponential distribution, and the deterministic equivalent transformation was presented through theorem (3.1) and corollary (3.1). Then, we proposed an extension to later approach to deal with two-parameter exponential input coefficients under the assumption of dependence, and the deterministic equivalent transformation was presented in theorem (4.1) and corollary (4.1).

It was shown that the proposed extension of approach (2) for two-parameter exponential distribution is the general form of both approaches; approach (1) when the correlation coefficient is zero and $m = 2$, and approach (2) for single-parameter exponential distribution when the location parameters are zero.

Finally, two examples were provided to illustrate the procedures of the proposed approaches.

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