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Assessment of cooperative sugar factories in tamilnadu - a dea approach

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ABSTRACT

Data Envelopment Analysis (DEA) is a method of analyzing the relative efficiency of similar type of organizations known as Decision Making Units (DMUs). In this paper, DEA model is applied to evaluate the relative technical efficiency of Cooperative Sugar Factories in Tamil nadu during the period 2012-2013. We have considered 15 sugar factories functioning in the state. The variables chosen here to characterize production units are, Sugar cane crushed, Share capital as inputs and Sugar production as output. The BCC model is Output- oriented allowing for variable returns to scale (VRS), units are ranked based on peer count summary.

Keywords: *Data Envelopment Analysis (DEA), Decision Making Units (DMUs), Banker, Charnes, Cooper (BCC) Variable Returns to Scale (VRS).*

1. Introduction

1.1 Sugar Industry

The Sugar Industry in Tamil Nadu plays a vital role in the economic development of the State and particularly in rural areas. Tamil Nadu is one of the leading producers of sugar in the country and its contribution is about 7% of country‘s total sugar production. There are 46 sugar mills in Tamil Nadu of which 16 sugar mills are in cooperative sector, 3 in public sector and 27 in private sector. At present 44 sugar mills are functioning and the remaining 2 mills viz., Madura Sugars and Arunachalam Sugar Mills Ltd., are not functioning. There have been gradual improvements in the cane yield and sucrose content of sugarcane in the state due to elaborate extension activities taken up by the sugar mills and Research and Development Institutions. To make sugar industry more profitable, has decided to set up cogeneration plants in 12 sugar mills (10 cooperative 2 public sector sugar mills). Along with Co-generation, to reduce the power and steam Consumption by the sugar mills and also to export more Power to Tamil Nadu Electricity Board Grid, it has been decided to modernize the above 12 sugar mills. Ethanol-cum-Distillery Plants is being established at Cheyyar cooperative sugar mills. The production of sugar in the entire country compared with the production of Sugar in Tamil Nadu for the past 5 crushing seasons and the estimated production of Tamil Nadu.

1.2 Sugar by Products

(i) Co-generation

At present 3 co-generation plants are functioning in M.R.Krishnamurthy cooperative sugar mills, Cheyyar co-operative sugar mills with an installed capacity of 7.50MW each and Subramania Siva Co-operative Sugar Mills with an installed capacity of 5.00MW.

For the accounting year 2010-11, these sugar mills have exported power to Tamil Nadu Electricity Board.

(ii) Bagasse

The sugar mills use bagasse, a byproduct, as fuel to generate steam for operating the mills. Surplus bagasse is being sold to other users on tender basis.

(iii) Molasses

Molasses is a valuable downstream by-product of sugar mills and sold by conducting tender-cum-auction through Tamil Nadu Co-operative Sugar Federation Limited. This motivated the researcher to analyze the efficient functioning of Cooperative Sugar factories in Tamil nadu.

1.3Productivity and Efficiency

Productivity is a measure of output from a production process, per unit of input. For example, labor productivity is typically measured as a ratio of output per labor-hour, an input.

1.4 Meaning of DEA

Data Envelopment Analysis (DEA) is a nonparametric linear programming technique that can be used to compare the relative performance of Decision Making Units (DMUs) operating under comparable conditions and ranking DMUs It is particularly effective in handling complex processes where DMUs use multiple inputs to produce multiple outputs. Unlike parametric methodologies which assume that the same average equation applies to all observations or DMUs, DEA –optimizes‖ each DMU, arriving at an efficiency score for every DMU relative to the entire sample.

1.5 Objective of the Study

- To study the Relative Efficiency of 15 Co-operative Sugar Factories in Tamil nadu through BCC (1984) model.
- Identification of Efficient and Inefficient Factories based on the Efficiency scores
- To construct the Peer group for the inefficient factories so that the inefficient factories could compare its Input and Output and then to attain Efficiency
- Ranking of DMUs based on Peer counts

2. Review of Literature

Farrel (1957) is considered to be the most influential paper on DEA. The further pioneering contributions were made by CCR (1978, 1979) and CCR (1981). Banker, Charnes and Cooper (1984) and Charnes et al (1985). Banker and Morey (1986) have evaluated the relative technical and scale efficiencies of DMUs by means of mathematical programming formulations when some of the inputs and outputs are exogenously fixed and beyond the discretionary control of DMU personnel. Bhattacharayya et al. (1997) Saha and Ravishankar (2000), Tone Kaoru (2001) proposed a slacks-based measure of efficiency in DEA and stated that this measure has a close connection to BCC measure of efficiency. Leleu (2006) studied DEA in the context of continuous optimization using BCC models. Asmild et al (2007) developed procedures for measuring overall efficiency and effectiveness using DEA. Performance measure illustrated by Chetchotsak and Kaiser (2002) is an example of using DEA to measure efficiency and effectives. Their work measures performance of a peer of bus transit branches. A DEA modes pro-posed by Singh (2006) is used to measure efficiency of sugar factories in India while the model proposed by Fernandez and Nuthall (2009) measures efficiency at farm level in the Philippines.

3. DEA Model

DEA converts multiple inputs and outputs into a scalar measure of efficiency. Production frontier/envelopment has Constant Returns to Scale in the CCR model meaning thereby that proportional increase in inputs result in a proportionate increase in outputs. BCC model identifies whether a DMU is operating in increasing, decreasing or constant returns to scale. The Decision Making Units under BCC model forms a convex combination by adding the convexity constraint $\sum_{n=1}^{N} \lambda_n = 1$

DEA can be either input or output oriented under constant as well as variable returns to scale (CRS and VRS). The technical scores obtained through input oriented and output oriented methods possess the similar values under constant returns to scale but differ under variable returns to scale technology. The present study estimated technical efficiency of cooperative sugar factories under output-oriented technique explaining that how much feasible output is a maximized with input held constant.

BCC Output oriented model

$$\begin{aligned} & Max\phi \\ s.t \quad & Y\lambda \geq \phi Y_0 \\ & X\lambda \leq X_0 \\ & \sum_{n=1}^{N} \lambda_n = 1 \\ & \lambda \geq 0, \end{aligned}$$

where ϕ = Efficiency Measure

X= $[X_1, X_2, \ldots, X_N]$ = Vector of Inputs

Y= $[Y_1, Y_2, \ldots, Y_N]$ = Vector of Outputs

$\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_N]$ = Vector of Weights

Y_0= output of the observed DMU

X_0= input of the observed DMU

N= Number of DMUs

Solving the above model it gives ϕ which is the optimal efficiency score satisfies $\phi \geq 1$, with $\phi = 1$ indicating efficient unit and $\phi > 1$ indicating extent of radial inefficient related to best practice DMU in the sample and simultaneously extent to which all outputs increased proportional with given input level to project inefficient DMU onto frontier.

4. Data and Empirical Analysis

In this paper secondary data collected from department of Sugar in Tamil nadu during the period 2012-2013.We have consider 15 Cooperative Sugar factories in Tamil nadu. Here each Sugar factories is considered as DMUs listed below,

Ambur	Dharmapuri	Tiruttani	Subramaniya Siva
Amaravathi	Vellore	NPKRR	Kallakurichi - II
Salem	Thirupattur	M.R.K	National
Kallakurichi-I	Chengalrayan	Cheyyar	

For each DMU Sugar cane crushed, Share capital as inputs and Sugar production as output for this study.

Table1: ***Descriptive Statistics***

Variables	Mean	Std deviation	Minimum	Maximum
Sugar cane crushed	2.13	1.12	0.87	4.36
Share capital	1133.76	775.58	255.86	2564.17
Sugar production	0.19	0.11	0.06	0.38

The above table provides that there was high variation in capital and sugar product among the sugar producers. The duration of crushing season ranged from 0.87 to 4.36.

Table 2: Efficiency Scores and Peers

DMUs	Efficiency Score	Peers	Peer Count	Rank
Ambur	1.000		1	2
Amaravathi	1.123	Ambur,Dharmapuri,Thirupattur		
Salem	1.000		1	2
Kallakurichi-I	1.000			
Dharmapuri	1.000		7	1
Vellore	1.127	Dharmapuri,Thirupattur		
Thirupattur	1.000		7	1
Chengalrayan	1.178	Salem, Subramaniya Siva		
Tiruttani	1.000			
NPKRR	1.335	Dharmapuri, Thirupattur		
M.R.K	1.447	Dharmapuri, Thirupattur		
Cheyyar	1.257	Dharmapuri, Thirupattur		
Subramaniya Siva	1.000		1	2
Kallakurichi - II	1.212	Dharmapuri, Thirupattur		
National	1.137	Dharmapuri, Thirupattur		

The above gives the efficiency score and peers of each DMUs

5. Conclusion

In this paper observe that out of 15 Cooperative Sugar factories, 7 factories are efficient and remaining 8 factories are Inefficient. Inefficient factories can improve the efficiency with reference to its peer‛s. For example The Inefficient sugar factories Amaravathi can compare‛s its inputs and outputs data with the linear combination of Ambur, Dharmapuri and Thirupattur.. Further it is observed that few efficient sugar factories are acting as Peer to many inefficient factories. Peer group known as reference set gives input and output targets to the inefficient DMUs for improving their efficiency. According to the peer count summary it‛s found that Dharmapuri and Thirupattur factories stood rank one, Ambur,salem and Subramaniya Siva factories stood rank two.

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FUZZY LOGISTIC REGRESSIONFOR THE DETERMINANTS OF CHILD MORTALITY

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Abstract:

Infant Mortality Rate is a measure of the annual rate of death in children less than one year old and is a sensitive indicator of living and socio - economic conditions of individuals in a country. National Family Health Survey NFHS -3, (2005-06) is a large scale survey conducted every 6 years with respondents being ever married women in the age groups 15-49 years and records survival status of infants, infant age at death in months along with socio-demographic factors like residence, religion, mother‘s age, age at first marriage, gender of infant,birth order, and birth weight .In this paper the Infant survival time (IST) is categorised as and the possibilistic odds of survival expressed as a symmetric fuzzy number is modelled as a function of the determinnats of child mortality using fuzzy logistic regression (Pourahmad etal (2011)).The model parameters are estimated using fuzzy linear regression approach by Tanaka etal (1982,1987) .

The model is evaluated by a goodness of fit index.s

Keywords: Fuzzy logistic regression, Fuzzy number, NFHS -3(2005-06).

1. Introduction:

Today‘s Children are the citizen of future society and are highly treasured assets to the nation and it‘s everyone rights to concentrate in their health. Demographic surveys provides state and national-level information on fertility, family planning, infant and child mortality, maternal and child health, nutrition of woman and children, etc. Infant Mortality Rate is a measure of the annual rate of death in children less than one year old and is a sensitive indicator of living and socio - economic conditions of individuals in a country. Socio economic factors like residence, religion, gender and biological factors mother‘s age, birth order, age at first marriage and birth weight are some of the determinants of child mortality.So far past researches have focussed on building statistical models for these risk factors. Das and Lee (2008), Das (2011) have identified the risk factors of infant survival time by the joint GLM approach,S.Santhana Lakshmi and R.Geetha (2017) have used Tweedie model to make a comparative assessment on socio demographic factors of child mortality across various states in India.These models are more appropriate when the relationship between the response and the explanatory variables is crisp. In real life situation vagueness or uncertainty in the observations may require decision making in a fuzzy environment.Tanaka (1982, 1987), Tanaka &Watada (1988, 1989), Hsiao- Fan Wang et al (2000) introduced fuzzy linear regression model as a linear programming problem to determine the regression coefficient as fuzzy numbers. Luiz Fernando C. Nascimento et al. (2009) in a study undertaken in Brazil, use fuzzy linguistic model to analyse the risk factor on neonatal death based on birthweight, gestational age and Apgar score.

A discussion on fuzzy logistic regression is found in papers by Ramadan Hamed et al (2009), S. Pourahmad et al (2011).S. Mahmoud Taheri et al (2014). In this paper an attempt is made to develop a fuzzy logistic regression model (FLRM) with fuzzy membership function for the binary response variable- Infant survival time.

The rest of the paper is organized as follows. In Section 2 concept of logistic regression, possibilistic odds and FLRM are discussed. Section 3 presents the methods and findings based on NFHS -3 data and results are given in Section 4.

2. Logistic Regression:

Logistic model is a very powerful statistical technique extensively used in medical research to model the binary response variable on a set of explanatory variables ,with a probability of success .
The relationship between the predictors and the response variable is given by thelogit transformation of as

$$—— \quad (\quad)$$

when vagueness is present in the binary response variables, the probability of success = cannot be calculated and modelled exactly. In such cases another term to describe the aspect of uncertainty called –possiblistic odds‖ can be used.

Possibilistic Odds:
Let i= 1, . . . ,n be the possibility of success, ... It can be defined as
(i) or (ii) A linguistic term, These terms should be defined in such a way that the union of their supports cover the whole range of (0, 1).
(ii) The ratio / i = 1 ..... ,n is considered as possibility odds of the ith case which detects the possibility of success relative to the possibility of non – success.

2.1. Fuzzy logistic regression analysis

Fuzzy linear regression introduced by Tanaka et al. (1982) is a non-parametric method which aims to model vague and imprecise phenomena using fuzzy model parameters. Consider the data set , i= 1,2,…,n where X_i is the vector of crisp observation on the independent variables for the ithcase. The response observation is a number in [0, 1] and indicates the possibility of ith case.
The basic fuzzy logistic regression model is
˜ ˜ --------- (1)
Where X = $(X_1, X_2, \ldots, X_N)^T$is a vector of independent non- fuzzy variables, Ã = is a vector of fuzzy coefficient presented in the form of triangular fuzzy numbers denoted by with its membership function described as,

$$( ) \qquad \frac{|\quad|}{\qquad}$$

Where is the central value, is the spread value and ˜ / is the estimator of the logarithmic transformation of possibilistic odds

The fuzzy parameters are determined by minimizing the total sum of the spreads of the estimated values for a certain measure of goodness of fit h-level, using the linear programming problem.

$\Sigma \quad \Sigma \qquad | \, |$ ------------ (2)

Subject to the constraints

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$$\Sigma \qquad\qquad \Sigma \quad | \quad |$$

and are free variables.

LP solver is used to estimate the parameters.
The coefficient of determination is used as a measure of goodness of fit.

3.**Methods and Findings:**

Data: The data used in the present study are from National Family Health Survey (NFHS-3), 2005-06a large scale household survey conducted every 6 years across 29 states which cover 257682 ever married women in the aged groups (15-49) years. In this paper the data is extracted from 3349 women from Sikkim to model IMR based on the Fuzzy logistic regression model with seven predictors of child mortality.

Description of covariates and levels
Dependent Variable: The dependent variable for study is the infant survival time. Age at death measured in (months).
Independent Variable: The maternal factors :-1.Mothers age (Mage) 2. Birth Order (BORD) **3.** Age at first marriage 4. Infant birth weight .Household/community factors:- 1. Place of residence 2. Religion and 3. Gender are taken as independent variables. The covariates are categorised in Table 1.

Table1.Categorisation of Variables in the Analysis

Domain/Variable Name		**Description**
Household/ Community	Place of residence	Urban-1,Rural -2
	Gender	Male -1 , Female -2
	Religion	Hindu -1,others-2
Maternal factors	Age at First Marriage	In Years
	Birth Order (BORD)	Parity
	Mother's age (Mage)	In years
	Infant birth weight	In Kilograms
Dependent Variable	Infant survival time	Age at death in Months

Data sources- NFHS-3 (2005-06).

Methodology and Formulation:

Consider the data set =), i=1,2,…,M where is the vector of crisp observations on the independent variables like mothers age , birth order, infant birth weight, age at first marriage, residence, sex, religion and the dependent variables is the infant survival time(IST).It is categorized as IST >1 and IST 1. The response probabilities are assumed as symmetric triangular fuzzy numbers and the fuzzy logistic regression model is given by

For illustration purpose we have taken a sample of 35 records and using LP Solver tools the following results are obtained for different h values .The objective function for h=0.5 is

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=

This function should be minimized with respect to 70 constraints (35 observations × 2).
Using LP Solver, the above linear programming problem was solved and the coefficients are estimated as follows. The constraints corresponding to the first record is given below

=-1.66, = 0, = -0.069, = 0.422, = 0.441, = -1.16, = -0.40, = 0.037, = 0,
= 0, =0.008, =0, = 0.001, = 0.050, = 0, = 0.023,

The fuzzy logistic regression model with an optimal value of Z= 7.544 is
˜ = (-1.66, 0) X0 + (0, 0) Residence + (-0.069, 0) Religion + (0.422, 0) Sex + (0.441, 0.001) Mother‘s age + (-1.16, 0.050) Birth Order + (-0.40,0) Age at First Marriage + (0.037, 0.023) Birth Weight
Table 2 gives the estimated fuzzy coefficients for h=0.4,0.5 and 0.6

Table 2. The Estimated parameter for Fuzzy logistic Regression analysis

H									Z
0.4	(-1.66,0)	(0,0)	(0.069,0)	(0.422,0)	(0.441,0.001)	(-1.16, 0.041)	(-0.40,0)	(0.037,0.019)	6.295
0.5	(-1.66,0	(0,0)	(-0.069,0)	(0.422,0)	(0.441,0.001)	(-1.16, 0.050)	(-0.40,0)	(0.037,0.023)	7.544
0.6	(-1.66,0	(0,0)	(0.069,0)	(0.422,0)	(0.441,0.002)	(-1.16, 0.062)	(-0.40,0)	(0.037,0.029)	9.443

The values of possibilistic odds, centre, spread, lower and upper boundis given in table 3.

Table: 3 Fuzzylogistic RegressionEstimators

S.No	Possibilisticodds	Centre	Lower	Upper	Spread	S.No	Possibilisticodds	Centre	Lower	Upper	Spread
1	0.67	0.971	0.823	1.119	0.148	19	0.99	4.865	4.588	5.142	0.277
2	0.54	0.215	0.074	0.356	0.141	20	0.92	2.692	2.443	2.941	0.249
3	0.99	4.575	4.297	4.853	0.278	21	0.77	1.338	1.118	1.558	0.22
4	0.71	1.213	1.037	1.389	0.176	22	0.28	-0.738	-0.95	-0.521	0.217
5	0.63	0.611	0.448	0.774	0.163	23	0.64	0.77	0.649	0.891	0.121
6	0.82	1.767	1.597	1.937	0.17	24	0.59	0.502	0.354	0.65	0.148
7	0.63	0.721	0.557	0.885	0.164	25	0.53	0.394	0.191	0.597	0.203
8	0.55	0.379	0.115	0.643	0.264	26	0.6	0.694	0.543	0.845	0.151
9	0.25	-0.884	-1.119	-0.649	0.235	27	0.22	-1.121	-1.26	-0.985	0.136
10	0.47	0.197	-0.109	0.503	0.306	28	0.52	0.258	0.095	0.421	0.163
11	0.33	-0.697	-0.88	-0.514	0.183	29	0.48	0.194	0.067	0.321	0.127
12	0.94	2.939	2.649	3.229	0.29	30	0.65	0.848	0.703	0.993	0.145
13	0.62	0.624	0.424	0.824	0.2	31	0.65	0.818	0.629	1.007	0.189
14	0.69	1.052	0.853	1.251	0.199	32	0.73	1.218	1.029	1.407	0.189
15	0.24	-1.017	-1.183	-0.851	0.166	33	0.23	-1.043	-1.2	-0.883	0.16
16	0.61	0.639	0.477	0.801	0.162	34	0.41	-0.179	-0.32	-0.039	0.14
17	0.98	3.95	3.601	4.299	0.349	35	0.53	0.32	0.107	0.533	0.213
18	0.97	3.518	3.32	3.716	0.198	R^2 =0.95					

Conclusion:

In this papera fuzzy logistic regressionis discussed which can be used in cases where the explanatory variables are crisp observation but the values of the binary response variable are fuzzy .The possibilistic odds of Infant survival time(IST>1) is modelled as a function of the determinants of child mortality. A symmetric triangular membership function is assumed for the Infant survival time (IST) and the fuzzy parameters are estimated by the linear programming approach proposed by Tanaka. The proposed model explains 95% of variability in fuzzy infant survival time and can be used to model vagueness in binary responses.

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