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Optimization of Financial Performance of Software Companies through Response Surface Methodology in Fuzzy Environment

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Abstract: In this paper, financial performance of software companies is considered as response to optimize the financial ratios simultaneously by considering the triangular fuzzy numbers of financial ratios. Response surface methodology is implemented to maximize the financial performance of these companies. Rankings of the companies, obtained through proposed methods are considered as responses. Fuzzy financial ratios, evaluation method and possibility level are considered as factors to implement RSM.

I. INTRODUCTION

Software sector has a crucial role in the economic growth of a country. Financial performances of SWCs have been linked with development of the economies of a country. Financial performance is the primary goal of all business ventures, which is important for viability in the long-run. In this respect, it is extremely important to evaluate past, current and future profitability, in order to predict and avoid negative consequences.

The financial performance indicators, i.e. financial ratios are not enough to measure the performance of banks. Alternative multi-criteria decision making methods are necessary for performance evaluation and ranking of business organizations. Knowing the financial performance of organizations is not only sufficient but also requires statistical analysis to establish the relationship between financial performance and the financial ratios. Response surface methodology (RSM) is a collection of tools for fitting a surface to special set of data, and determining optimum factor levels is also part of methodology and uses a regression model for optimization of given response. In general, crisp values for factors are considered and response surface methodology is implemented. But in practice, the factors are fuzzy in nature. Fuzzy logic is an approach used to formalize the uncertain or approximate reasoning.

In this research, data on nine financial ratios of eighteen software companies during five financial years is considered and triangular fuzzy number is formulated. These triangular fuzzy numbers are defuzzified into crisp values and RSM is implemented to obtain factor settings to maximize financial performance of the companies. The response surface methodology (RSM) is a widely used mathematical and statistical method for modelling and analyzing a process in which the response of interest is affected by various variables and the objective of this method is to optimize the response. The parameters that affect the process are called dependent variables or factors, while the responses are also called dependent variables. It is necessary to analyze financial performance of SWCs to determine optimum financial ratios through response surface methodology.

II. LITERATURE REVIEW

ElhamShadkam and Mehdi Bijari (2015) considered DEA, RSM and Cuckoo algorithm and presented a combinatory algorithm called DRC in which one response surface function for efficiency is obtained instead of a multi-response surface functions for each response.

Allen et.al, (2015) proposed 'low-cost response surface methods' (LCRSMs) that typically require half the experimental runs of standard response surface methods based on central composite and Box Behnken designs, but yield comparable or lower modelling errors under realistic assumptions.

Hung-Yi Wu et al., (2019) proposed a Fuzzy Multiple Criteria Decision Making (FMCDM) approach for banking performance evaluation. Drawing on the four perspectives of a Balanced Scorecard (BSC), this research first summarized the evaluation indexes synthesized from the literature relating to banking performance.

Mahdi Bashiri et al., (2009) proposed Optimization of multi response surface (MRS) in robust designs is proposed and applied to determine optimum characteristics of a process in a satisfactory region and reduce variation of responses simultaneously by applying fuzzy set theory.

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Boyac et al., (2017) developed fuzzy mathematical model using a multi-response surface methodology with fuzzy logic to optimize all response variables simultaneously.
AlevYükselAydar (2018) used response surface methodology in extraction of plant material in high yield and quality and determined optimum conditions for this extraction process.
D.Vijayan and V. Seshagiri Rao (2017) optimized the process parameters of friction stir welding using AA2024 and AA6061 using response surface method (RSM) based fuzzy grey relational approach (Fuzzy - GRA).
Vipul et al. (2013) used Central composite design and response surface methodology (RSM) to optimize the dosage level of talc and CPAM to get the variation of ash. Results showed that both independent variables talk and CPAM have significant effect on increasing the ash.
GökhanOrhan et al. (2011), investigated deposition parameters such as current density, electrolyte composition (Cu/Zn mole ratio), mechanical stirring speed, and temperature on the Cu content of alloy powder and cathodic current efficiency using the response surface methodology.
Giovanilton etal. (2011), studied transesterification of soybean oil with ethanol. The transesterification process can be affected by differing parameters. The biodiesel production process was optimized by the application of factorial design 24 and response surface methodology.
Yong Wang et al. (2018) adopted Response surface methodology to optimize the preparation conditions of soy-based adhesives (SBAs).The parameters such as the effects and interactions of water borne poly urethane (WPU) addition level,temperature and time on wet shear strength were investigated.
Dayananda Pai et al. (2010), made a study to optimize machining parameters on surface roughness in the grinding of 6061Al-SiC25P (MMCs). In the study, hardness flow rate of the coolant and depth of cut were chosen for evaluation by the response surface methodology.
Saeid G. Jafarzadeh et al. (2012), employed multiple regression which uses response surface quadratic methodology to minimize the costs associated with delay of orders, the number vehicles used in the transportation, fuel as well as labour cost.
Aneirson Francisco da Silva et al. (2019), proposed a new procedure that considers the insertion of uncertainties in the coefficients of this empirical function, which is what generally occurs, in practical experimental problems. The new procedure was applied to a real case related to a stamping process in an automotive company.
Jen S. Shang et al. (2004),proposed a hybrid approach that incorporates simulation, Taguchi techniques, and response surface methodology for identifying the 'best' operating conditions for a supply chain.
Pak R. (2016), attempted to combine both IPA and RSM in order to enhance the satisfaction of online courses in preparing for the college entrance examination in Korea.
MasoudShariati-Rad et al. (2018) employed response surface methodology to explore the factors influencing the response, i.e. concentration of 1,10-phenanthroline and concentration of as-synthesized carbon dots(CDs).
Linda Rhoades et al. (2010), examined the extent to which combinations of two predictor variables relate to an outcome variable when the discrepancies in perceived supervisor and organizational support relate to affective commitment using polynomial regression with response surface analysis.

III. RESPONSE SURFACE METHODOLOGY

Response surface methods are used to examine the relationship between one or more response variables and a set of quantitative experimental variables or factors. These methods are often employed after you have identified a "vital few" controllable factors and you want to find the factor settings that optimize the response. Allen and Yu (2002) extended RSM with novel low-cost response surface methods (LCRSMs). Candioti et al. (2014) presented methods and application of RSM when several responses have to be simultaneously optimized and classified methods to two category, graphical optimization and Desirability function. Designs of this type are usually chosen when there is suspect of curvature in the response surface. Response surface methods may be employed

- Find factor settings (operating conditions) that produce the "best" response
- Find factor settings that satisfy operating or process specifications
- Identify new operating conditions that produce demonstrated improvement in product quality over the quality achieved by current conditions
- Model a relationship between the quantitative factors and the response

Response Surface Methodology (RSM) was used to optimize and evaluate main effects, interaction effects and quadratic effects of the financial ratios and their settings on financial performance of eighteen software companies. The data on financial ratios during the financial years 2013-14 to 2017-18 of eighteen software companies listed in BSE are considered as input factors and corresponding rankings of financial performance determined through fuzzy four phased method and Fuzzy GRA-DEAare considered as responses to implement RSM.

Response surface designs are defined using Design Expert 12. The relationship between response in terms of rank of financial performance and the financial ratios as input factors is modelled through response surface design. The response surface equation of performance is developed and utilized to find the factors (financial ratios) settings that produce the best response in terms of rank of the financial performance of the SWCs.

3.1 Illustration of the methodology –

The methodology is explained in the following steps.
Step1:Obtain the data on financial ratios
Data on nine financial ratios for eighteen software companies is obtained from annual reports from FY 2013-14 to FY 2017-18.
Step2: Develop triangular fuzzy numbers of financial ratios
Optimistic, mean and pessimistic values of each financial ratio are derived from the data of five financial years and triangular fuzzy number is formulated for each financial ratio of the SWCs.
Step3: Obtain rank of financial performance of SWCs
Financial performance of SWCs is evaluated by implementing Fuzzy four phased DEA and Fuzzy GRA-DEA methods.
Step4: Experiments for response surface analysis
The following design parameters are considered in the study
Type of Design: Response Surface Design
Experimental Option: Historical data
Number of Numeric Factors: 9 financial ratios
Number of levels of each Factor: Three(Minimum, Average and Maximum values);
Number of other numeric Factors: 1(Possibility Level)
Number of levels of each Factor: Two (0 and 1.0);
Number of Category Factors: 1(Performance Evaluation Method);
Number of levels of each Category Factor: Two (Fuzzy Four Phased DEA and Fuzzy GRA-DEA);
Number of Runs: 144
Regression Equation Model: Quadratic
Number of Responses:1 (Financial Performance Rank)
Step 5:Significance of model terms
The significance of model terms (financial ratios) on financial performance is evaluated by the F–test using Analysis of variance (ANOVA).
Step6:Optimization of financial performance
The levels of financial ratios for optimum financial performance is obtained using numerical optimization feature of the Design Expert software. The program searches for a combination of factor levels that simultaneously satisfy the requirements placed on each of the responses and factors. Desirability analysis was also performed by employing the design expert software to determine the optimum condition for the response of composite ranking. Based on the results the optimum factor settings of composite rank of financial soundness are specified.

IV. CASE STUDY

Nine financial ratios of 18 software companies during five financial years (FY 2013-14 to FY 2017-18) as discussed in the case study presentedare considered. Response surface methodology as discussed in section 3.2.1 is implemented to know the benchmarking values of financial ratios. Required data to conduct response surface analysis is presented in Table-1.

Table-1: Average Values of Financial Ratios

Software company	Stockholders equity ratio (FR1)	Turnover rate of accounts receivables (FR2)	Turnover rate of inventory (FR3)	Return of stockholder equity (FR4)	Quick ratio (FR5)	Operating income ratio (FR6)	Operating cash flow ratio (FR7)	Return of assets (FR8)	Market share (FR9)
SWC1	0.4835	5.8657	1071.0390	-0.5958	0.4487	-0.0368	0.1244	-0.1191	0.0038
SWC2	0.0063	5.6527	153.4263	30.7891	2.3799	0.2270	0.6032	0.1867	0.1252
SWC3	0.0112	5.9329	3178.4408	19.5916	4.1768	0.2722	0.7303	0.1842	0.1935
SWC4	0.0159	4.5723	363.1890	6.6993	1.8083	0.1180	0.5084	0.1066	0.0101
SWC5	0.0170	6.6350	1284.0541	3.2239	2.5205	0.0753	0.3096	0.0499	0.0025

SWC6	0.0389	5.6359	1228.7885	5.2961	3.0064	0.1692	0.7537	0.1712	0.0138
SWC7	0.0287	8.0097	1813.4911	3.1501	3.4431	0.1563	0.5657	0.0898	0.0169
SWC8	0.0274	4.8101	3451.3026	3.7416	2.1626	0.1615	0.4399	0.1005	0.0084
SWC9	0.0065	5.6263	1542.9972	28.4322	4.3278	0.3908	0.6142	0.1832	0.0133
SWC10	0.0342	6.0779	1253.5642	4.2276	3.6714	0.1873	0.7130	0.1398	0.0074
SWC11	0.0177	2.6234	183.4787	0.9567	0.4572	0.3149	0.1419	0.0188	0.0103
SWC12	0.0315	5.5766	505.0253	5.8860	4.9653	0.0479	1.0348	0.1759	0.0015
SWC13	0.0113	6.4123	757.7908	13.7595	1.9409	0.0874	0.4018	0.1460	0.0063
SWC14	0.0023	5.0137	4190.0039	118.2106	3.9594	0.2773	1.0799	0.2648	0.3333
SWC15	0.0611	5.4071	3408.2780	4.0310	2.7842	0.2178	0.7857	0.2321	0.0033
SWC16	0.0179	5.2446	813.7534	8.0653	2.0701	0.1731	0.3880	0.1376	0.0807
SWC17	0.0085	5.4578	103.8384	15.6016	2.0906	0.2093	0.5367	0.1263	0.1606
SWC18	0.0236	6.0394	20.5325	5.6972	2.2980	0.1384	0.5424	0.1350	0.0090

Table-2:Fuzzy Data on Financial Ratios (Factors for response surface analysis)

Software Commpany	Triangular Fuzzy Numbers of Financial ratios																				
	FR1			FR2			FR3			FR4			FR5			FR6			FR7		
SWC1	0.1298	0.4835	0.9961	4.7757	5.8657	6.9077	836.6929	1071.0390	1689.2743	0.0001	1.0213	1.0213	0.3774	0.4487	0.5345	0.0001	0.6592	0.8532	0.0001	0.1535	0.3893
SWC2	0.0047	0.0063	0.0080	4.3669	5.6527	6.3151	116.0055	153.4263	201.6980	21.4782	32.4062	32.4062	2.1518	2.3799	2.4869	0.9097	0.9231	0.9460	0.3787	0.6324	0.7660
SWC3	0.0050	0.0112	0.0152	5.5390	5.9329	6.4964	1301.0146	1644.7311	3016.0000	13.4082	21.2087	21.2087	3.4819	4.1768	4.6421	0.9631	0.9682	0.9751	0.5554	0.7594	0.8798
SWC4	0.0138	0.0159	0.0172	4.3579	4.5723	4.7198	73.0530	363.1890	1350.6822	7.9184	8.3164	8.3164	1.5198	1.8083	2.0681	0.7973	0.8140	0.8362	0.2925	0.5375	0.7599
SWC5	0.0136	0.0170	0.0269	4.5697	6.6350	8.0919	1299.4242	1299.9061	1300.8451	2.8119	4.8410	4.8410	2.1025	2.5205	3.3349	0.7247	0.7713	0.8180	0.2468	0.3387	0.4941
SWC6	0.0199	0.0389	0.0506	5.4938	5.6359	5.7679	1299.7556	1300.4664	1301.4115	4.1088	6.9132	6.9132	2.3899	3.0064	3.8261	0.8305	0.8652	0.8972	0.5205	0.7829	0.9644
SWC7	0.0276	0.0287	0.0300	3.6304	8.0097	9.5450	1299.8089	1788.0141	2545.3073	3.0575	4.7672	4.7672	2.4361	3.4431	4.4497	0.8379	0.8523	0.8654	0.1757	0.5949	0.9415
SWC8	0.0228	0.0274	0.0331	4.0544	4.8101	5.6774	297.3188	3451.3026	8298.0000	3.4859	5.3587	5.3587	1.8866	2.1626	2.7036	0.8351	0.8575	0.8715	0.3187	0.4690	0.6361
SWC9	0.0043	0.0065	0.0074	5.2477	5.6263	6.0902	1299.1445	1301.9900	1307.6618	26.3843	30.0493	30.0493	1.8600	4.3278	9.2470	1.0700	1.0868	1.0961	0.4043	0.6433	0.9421
SWC10	0.0257	0.0342	0.0444	5.7189	6.0779	6.3758	1300.9625	1301.2332	1301.5781	5.0834	5.8447	5.8447	3.4367	3.6714	3.9706	0.8505	0.8834	0.9442	0.5549	0.7422	0.8772
SWC11	0.0145	0.0177	0.0221	1.9229	2.6234	3.4431	1297.3562	1297.5271	1297.6936	0.9776	2.5738	2.5738	0.3089	0.4572	0.6016	0.9849	1.0109	1.0477	0.0014	0.1711	0.3170
SWC12	0.0232	0.0315	0.0427	5.0058	5.5766	6.4312	146.0758	499.4580	1303.9958	4.0358	7.5031	7.5031	3.9531	4.9653	6.0674	0.5513	0.7439	0.8341	0.2885	1.0640	1.8402
SWC13	0.0084	0.0113	0.0160	5.3559	6.4123	8.9554	201.6851	751.4584	1466.2900	9.0097	15.3766	15.3766	1.6740	1.9409	2.2570	0.7596	0.7834	0.7957	0.2455	0.4309	0.5740
SWC14	0.0018	0.0023	0.0029	4.8818	5.0137	5.1768	3116.4230	4190.0039	4862.4259	99.4569	119.8277	119.8277	2.6936	3.9594	5.1366	0.9547	0.9733	1.0035	0.8651	1.1091	1.4628
SWC15	0.0432	0.0432	0.0611	5.0276	5.0276	5.4071	1301.3368	1301.3368	3408.6518	4.0291	4.0291	4.0291	1.8727	1.8727	2.7842	0.8733	0.8733	0.9138	0.5802	0.5802	0.8149
SWC16	0.0145	0.0179	0.0242	4.7352	5.2446	6.2134	410.4457	813.7534	1405.6346	7.0869	9.6824	9.6824	1.9674	2.0701	2.2918	0.8396	0.8691	0.9185	0.2787	0.4171	0.5218
SWC17	0.0059	0.0085	0.0116	5.3047	5.4578	5.7028	79.0081	103.8384	121.6289	10.4619	17.2187	17.2187	1.9927	2.0906	2.2232	0.8866	0.9054	0.9179	0.5191	0.5659	0.6076
SWC18	0.0193	0.0236	0.0295	5.2878	6.0394	6.7336	16.9201	20.5325	25.0863	6.8516	7.3143	7.3143	1.9696	2.2980	2.6411	0.8134	0.8344	0.8494	0.3474	0.5716	0.7932

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Table-3: Financial Performance Ranks (Response for response surface analysis)

SWCs	Possibility Level = 0		Possibility Level = 0.5		Possibility Level = 0.75		Possibility Level = 1.00	
	Fuzzy four phased DEA	Fuzzy GRA-DEA	Fuzzy four phased DEA	Fuzzy GRA-DEA	Fuzzy four phased DEA	Fuzzy GRA-DEA	Fuzzy four phased DEA	Fuzzy GRA-DEA
SWC1	18	4	18	8	18	13	18	16
SWC2	3	9	3	4	2	4	2	4
SWC3	4	2	4	2	4	2	4	2
SWC4	7	17	9	17	9	17	9	17
SWC5	16	15	16	15	16	16	15	15
SWC6	12	12	12	11	11	9	11	9
SWC7	15	8	13	7	13	6	13	6
SWC8	14	6	14	9	14	10	16	11
SWC9	2	3	2	3	3	3	3	3
SWC10	10	13	11	10	12	8	12	8
SWC11	17	18	17	18	17	18	17	18
SWC12	11	5	8	6	7	7	7	7
SWC13	6	11	6	14	6	14	6	13
SWC14	1	1	1	1	1	1	1	1
SWC15	13	7	15	12	15	12	14	12
SWC16	8	14	7	13	8	11	8	10
SWC17	5	10	5	5	5	5	5	5
SWC18	9	16	10	16	10	15	10	14

V. RESULTS AND DISCUSSION

Financial performances of eighteen software companies listed in BSE are analyzed and optimum values of financial ratios are derived through response surface methodology using the Design Expert Software (Version12). Fuzzy Data on financial ratios, Possibility level and Method of evaluation are considered as factors for response surface analysis. Financial performance rank obtained through proposed methods (Fuzzy Four Phased DEA and Fuzzy GRA-DEA) is considered as response. The results obtained by response surface methodology implemented through Design Expert 12.0 are discussed in the following sections.

5.1 Analysis of variance (ANOVA) –

The significance of model terms is evaluated by the F–test for analysis of variance (ANOVA). The ANOVA analysis for technical efficiency was shown in Table-4.

Table-4: ANOVA Results

Source	Sum of	df	Mean	F-value	p-value	Remarks
Model	1914.6857	36	53.1857	79.8437	0.0000	significant
(FR1)L	10.3474	1	10.3474	15.5337	0.0004	significant
(FR1)M	9.4302	1	9.4302	14.1569	0.0006	significant
(FR1)R	8.5147	1	8.5147	12.7825	0.0010	significant
(FR2)L	17.1856	1	17.1856	25.7995	0.0000	significant
(FR2)M	10.6294	1	10.6294	15.9572	0.0003	significant
(FR2)R	23.3793	1	23.3793	35.0976	0.0000	significant
(FR3)L	6.7303	1	6.7303	10.1037	0.0031	significant
(FR3)M	5.2263	1	5.2263	7.8459	0.0082	significant
(FR3)R	3.1983	1	3.1983	4.8013	0.0352	significant
(FR4)L	16.2161	1	16.2161	24.3440	0.0000	significant
(FR4)M	17.8229	1	17.8229	26.7562	0.0000	significant
(FR5)L	13.2557	1	13.2557	19.8998	0.0001	significant
(FR5)M	12.2961	1	12.2961	18.4591	0.0001	significant
(FR5)R	13.3328	1	13.3328	20.0155	0.0001	significant
(FR6)L	4.9466	1	4.9466	7.4259	0.0100	significant
(FR6)M	8.0159	1	8.0159	12.0337	0.0014	significant

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(FR6)R	15.7762	1	15.7762	23.6836	0.0000	significant
Residual	23.3143	35	0.6661			
Cor Total	1938	71				

The Model F-value of 79.84 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

P-values less than 0.0500 indicate model terms are significant. In this case Fuzzy financial ratios namely:FR1 (Stockholders equity ratio), FR2 (Turnover rate of accounts receivables), FR3 (Turnover rate of inventory), FR4(Return of stockholder equity), FR5 (Quick Ratio) and FR6(Operating income ratio) are statistically significant model terms. Values greater than 0.1000 indicate the model terms are not significant and are not shown in above table. Method of Evaluation and Possibility values are arrives as statistically not significant.

Table-5: Fit Statistics of the Model

Std. Dev.	0.8162	R-Squared	0.9880
Mean	9.59	Adj R-Squared	0.9756
C.V. %	8.59	Pred R-Squared	0.9001
PRESS	4.01	Adeq Precision	29.0561

The Predicted R^2 of 0.9001 is in reasonable agreement with the Adjusted R^2 of 0.9756; i.e. the difference is less than 0.2.Adeq Precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The ratio of 29.056 indicates an adequate signal. This model can be used to navigate the design space.Hence the generated model for the financial performance ranking could be deemed fit and adequate in representing the ranking of financial performance of software companies considered in the study

5.2 Validation of the model –

In the response surface method, the model that best represents how response is affected by factor variables is determined theoretically. However, experiments (numerical computations) are to be carried out to verify the reliability of the theoretically determined models under optimum conditions. Chi-Square test and t-tests are most commonly used to determine the difference between experimental and predicted values. Another method to evaluate the validation of model is to calculate experimental error between theoretical and experimental values. In this study, t-test is adopted to know the difference between actual ranks and predicted ranks of eighteen software companies. The t score is a ratio between the difference between two groups and the difference within the groups. The larger the t score, the more difference there is between groups.

Actual and predicted values for financial performance ranks obtained through Fuzzy four phased DEA method at different possibility values are presented in Table-6.

Table-6:Actual Rank and Predicted Rank Values through Fuzzy Four Phased DEA Method

SWCs	Alpha=0.0		Alpha=0.5		Alpha=0.75		Alpha=1.00	
	Actual Rank	Predicted Rank	Actual Rank	Predicted Rank	Actual Rank	Predicted Rank	Actual Rank	Predicted Rank
SWC1	18	4	18	9	18	12	18	16
SWC2	3	8	3	5	2	4	3	3
SWC3	4	2	4	2	4	2	5	2
SWC4	7	17	8	17	9	17	7	17
SWC5	16	15	16	15	15	15	16	15
SWC6	12	12	12	10	11	10	11	9
SWC7	15	8	13	7	13	6	17	6
SWC8	14	6	14	9	14	10	15	11
SWC9	2	3	2	3	3	3	2	3
SWC10	10	13	11	10	12	9	13	7
SWC11	17	18	17	18	17	18	4	18
SWC12	11	5	9	6	8	7	14	7
SWC13	6	11	6	13	6	13	10	14
SWC14	1	1	1	1	1	1	1	1
SWC15	13	8	15	10	16	12	9	13
SWC16	8	14	7	23	7	11	8	10

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SWC17	5	9	5	7	5	5	6	4
SWC18	9	16	10	15	10	15	12	14

From the results shown in table 6, Mean Squared Error (MSE) is determined at each possibility level. The MSE values of 0.53, 0.56, 0.25 and 0.91 are obtained for possibility values of 0, 0.5, 0.75 and 1.0 respectively.
Also, t test is conducted to know the difference between actual rank and predicted rank obtained through Fuzzy four phased methodology at different possibility levels. The t values of 0.04, 0.36, 0.06 and 0.04 are obtained at possibility levels of 0.0, 0.5, 0.75 and 1.0 respectively. The calculated t values are less than the tabulated value of 1.74 at given degrees of freedom with p-value of 0.05. Hence, the null hypothesis- there is no difference between actual and predicted values can be accepted.
Also, actual and predicted values for financial performance ranks obtained through Fuzzy GRA-DEA method at different possibility values are presented in Table-7.

Table-7:Actual Rank and Predicted Rank Values through Fuzzy GRA-DEA Method

SWCs	Alpha = 0.0		Alpha = 0.5		Alpha = 0.75		Alpha = 1.00	
	Actual Rank	Predicted Rank	Actual Rank	Predicted Rank	Actual Rank	Predicted Rank	Actual Rank	Predicted Rank
SWC1	4	4	13	12	13	12	16	16
SWC2	9	8	4	4	4	4	4	3
SWC3	2	2	2	2	2	2	2	2
SWC4	17	17	17	17	17	17	17	17
SWC5	15	15	16	15	16	15	15	15
SWC6	12	12	9	10	9	10	9	9
SWC7	8	9	6	6	6	6	6	6
SWC8	6	6	10	10	10	10	11	11
SWC9	3	3	3	3	3	3	3	3
SWC10	13	13	8	9	8	9	8	7
SWC11	18	18	18	18	18	18	18	18
SWC12	5	5	7	7	7	7	7	7
SWC13	11	11	14	13	14	13	13	14
SWC14	1	1	1	1	1	1	1	1
SWC15	7	7	12	12	12	12	12	13
SWC16	14	14	11	11	11	11	10	10
SWC17	10	10	5	5	5	5	5	4
SWC18	16	16	15	15	15	15	14	14

From the results shown in table 7, Mean Squared Error (MSE) is determined at each possibility level. The MSE values of 0.001, 0.02, 0.02 and 0.04 are obtained for possibility values of 0, 0.5, 0.75 and 1.0 respectively. These results confirmed that experimental values are in agreement with the predicted values, thus the model was validated.
The t-test is conducted to know the difference between actual rank and predicted rank obtained through Fuzzy GRA-DEA methodology at different possibility levels. The t values of 0.00, 0.44, 0.44 and 0.44 are obtained at possibility levels of 0.0, 0.5, 0.75 and 1.0 respectively. The calculated t values are less than the tabulated value of 1.74 at given degrees of freedom with p-value of 0.05. Hence, the null hypothesis- there is no difference between actual and predicted values can be accepted.

5.3 Desirability analysis –

Desired goal for response is considered as ‘rank less than 5’. And desirability analysis was performed by employing the design expert software using the desirability function for financial performance ranking values. Desirability values ranges from 0 to 1. ‘0’ indicates low desirability value where as ‘1’ is higher desirable value. From the desirability analysis, the optimal level of various financial ratios are found and listed in the table 8. Desirability level of 1.0 is obtained in the study.The following optimum fuzzy triangular numbers of the nine financial ratios are obtained and shown in Table-8.

Table-8: Optimal Levels of Various Financial Ratios

Financial Ratios	Optimum Fuzzy Triangular Number
FR1	(0.0018,0.0023,0.0029)
FR2	(4.8818,5.0137,5.1768)
FR3	(3116.4,4190.0,4862.4)
FR4	(99.45,119.83,119.83)
FR5	(2.6936,3.9594,5.1366)
FR6	(0.9547,0.9733,0.1.0035)
FR7	(0.8651,0.1.1091,1.4628)
FR8	(0.5904,0.6122,0.6329)
FR9	(0.3244,0.3333,0.3449)
Note: possibility level of1.00; Evaluation Method: Fuzzy GRA-DEA	

The optimal fuzzy triangular numbers of nine financial ratios obtained in the study are similar to the financial ratios of software company 14 (SWC14). Results obtained at the optimal combination were in agreement with the theoretical result. Therefore, the model obtained in this research was confirmed. Hence, the optimum values of financial ratios can be considered as benchmarking values to improve the financial performance of software companies.

VI. CONCLUSIONS

According to the relevant literature, most studies used financial factors to evaluate performance of business organizations. The present research proposed two fuzzy multi-criteria decision making evaluation models for performance evaluation of software companies enlisted in BSE. The proposed model considers financial ratios and optimizes the financial performance of software companies.

Response surface methodology with a wide range of applications in food science and technology has been successfully used for many years.In this study, fuzziness in the factors are considered and is used for modelling of the response is made through conventional response surface methodology. Further, RSM methodology is implemented to the multi-criteria decision making applications of industrial engineering. One of the most important points in the implementation of this method is that the predicted values in the model are verified mathematically. RSM has many advantages when compared to classical methods. It takes care of historical data to study the effects of all the factors and the optimum combination of all the variables with triangular fuzziness is revealed. It also requires less time and effort. With all of these advantages, it will be used not only in chemical engineering, pharmacy and other engineering sciences but also in other areas of industrial engineering and management. The interaction behaviour between factors may further analyze in future studies.

VII. REFERENCES

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