NAU Journal of Civil Engineering (NAUJCVE) November/December 2023
Nnamdi Azikiwe University Journal of Civil Engineering (NAUJCVE)

Volume-1, Issue-4, pp-41-51
www.naujcve.com
Research Paper Open Access

Experimental Approach for Optimal Location of Speed Bumps Using Classical Design of Experiment Method

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Abstract: *The optimal placement of speed bumps play a crucial role in traffic management and ensuring safety on roadways. This study investigated the ideal location for speed bumps using experimental approach based on the classical design of experiment method. The effects of the independent process variables; number of passengers (1 - 5 passengers), car speed (5 - 30 m/s), surface inclination (0 – 7 degree) and the response variable, (distance of bump placement) were optimized to improve the process. The process parameters were analyzed and optimized through a set of experiments designed by central composite design (CCD) using response surface methodology (RSM) procedure in the DESIGN EXPERT environment. The obtained statistical model was found to be suitable for predicting the optimum distance of the speed bump from the stop point. Statistical checks were done on the model using least square method, ANOVA and T-test. The Optimum condition of distance was obtained from the combination where all the process variables were maximum i.e. Number of passengers (5 passengers), car speed (30 m/s) and surface inclination (7 degree). The distance during optimum treatment was observed to be approximately 16.66m. The optimized parameters were verified and validated through a validation experiment, which concurs with the predicted optimal value in the design of experiment and also in line with the recommended standards used for the study.*

KEYWORDS**:** *Speed bumps, Classical Design of Experiments (DOE), Response Surface method (RSM), ANOVA, Central Composite Design (CCD*

Date of Submission: 10-11-2023 Date of acceptance: 12-11-2023

I INTRODUCTION

Major modern highways that connect cities in populous developed and developing countries usually incorporate features intended to enhance the road's capacity, efficiency, and safety to various degrees [1].To ensure that the required speeds are maintained, it is practice to provide certain control measures. These measures can ensure improved traffic movement with better safety and convenience [2]. However, at certain location such as approaches to manned and unmanned level crossings, sharp curves, accident prone locations, congested residential streets; control of speed may become necessary to allow smooth flow of traffic [3]. Speed bumps (also called speed breakers, or a sleeping policeman) are the common name for a family of traffic calming devices that use vertical deflection to slow motor-vehicle traffic in order to improve safety conditions. In Nigeria, like in many other countries, the law prohibits the construction of speed bumps on highways and it is only with government approval that bumps should be erected even in residential areas [4]. They can be designed to achieve a desired speed (e.g. 15 mph), which drivers are physically compelled to meet [5]. According to [6], speed bumps are commonly perceived as an effective method in reducing traffic speed for their easy installation and low cost.

The design of experiment technique is an efficient and cost-effective way to model and analyze the interactions which indicate process variations also has wide application in the improvement of new processes in such a way that processes can be defined based on several controllable variables [7]. With the application of designed experiments, engineers can make sure which subdivision of the process variables has the most significant influence on the process performance. **RSM** is a collection of mathematical and statistical techniques that are useful for modeling and analysis of problems in which output or response is influenced by several input variables and the objective is to find the correlation between the response and the variables investigated [8]. (Box and Wilson, 1954) proposed the Response Surface Methodology (RSM) for determining the operating conditions of chemical process with optimization of a specific response. In order to develop the response surface model, firstly the function must be assumed as a mathematical polynomial form having coefficients that should be determined. And then these coefficients are determined with applying the set of the experimental results. Matching a response surface design uses different designs for each model. In RSM there are two designs; namely, Central Composite Design (CCD) and Box-Behnken Design [10]. Central composite design (CCD) of RSM is one of the most popular tools used in optimization process condition. It essentially includes a full or fractional factorial design with center points that are augmented with a group of axial points that allow estimation of the curvature in the resulting model [11, 12]. In this paper, a 2-level 3 factors central composite design (CCD) was utilized for the designing and analysis of the experiment. According to the CCD, a 2-level 3 factors design was employed and total numbers of 20 experiments were performed in this case. The results were fitted to the following second order polynomial equation to predict the optimum distance conditions.

RSM is one of the Design of Experiments (DOE) methods used to approximate an unknown function for which only a few values are computed. These relations are then modelled by using least square error fitting of the response surface [13]. This study will guide in the efficient installation of speed bumps to help improve safety (by reducing road traffic crashes) along every road segments on which it is adopted.

II. MATERIALS AND METHODS

The data utilized in this study were gotten from on-field studies using equipment such as a Toyota Corolla (2010 model), note pad, chronometer, clinometer, odometer and measuring tape. The study was specifically conducted at P.C.E. Dunkwu street in Okpanam Metropolis of Oshimili-North Local Government Area of Delta State, Nigeria. The street composes of a single carriageway located within a residential area consisting of a 200mm lateritic sub-base and base, 60mm asphaltic concrete binder, a 40mm asphaltic concrete surfacing, concrete-lined drains, concrete kerbs and speed bumps using the case study research approach [11]. The study area is particularly defined by Geographical coordinates 6° 13' 39.3"N to 6° 13' 40.2"N and Longitude 6° 39' 27.8"E to 6° 39' 28.2"E.

A. Methods

Modelling the experimental design was performed by defining factors, factor ranges, and the objective. The factors were grouped into independent affecting factors and dependent factors. The car speed before bump, number of passengers and surface inclination are the independent affecting factors while the uncontrollable variables like car brake quality, climate condition and the road friction were not considered in this study. The impacts of these identified independent factors were examined and classified into various levels for which, an experimental design was developed using Design Expert® software. The range and level of the experimental variables used for statistical design of experiment are presented in Table 1 below.

Table 1: Range and Levels of independent variables

Independent Variables	**Range and Levels of Input Variables**	
	Lower Range (-1)	**Upper Range (+1)**
No. of Passengers (Nil) X_1	1	5
Car Speed (m/s) X_2	5	30
Surface Inclination (degree) X_3	0	7
Dependent Variable		
Distance (m) Y_1		

Using the range and levels of the independent variables presented in Table 1, statistical design of experiment (DOE) using central composite design (CCD) method was done. Experimental design was done with the aid of design expert version 7.01. The total number of experimental runs that can be generated using the CCD is defined as;

$$N = 2^n + n_o + 2n \tag{1}$$

Where;
N; is the number of experimental runs based on CCD design

2^n; is the number of factorial points
n_0; is the number of center points
2n; is the number of axial points
n; is the number of variables

Based on the DOE, an experimental design matrix having six (6) center points, six (6) axial points and eight (8) factorial points resulting to twenty (20) experimental runs was generated. Statistical design of experiment (DOE) using the central composite design method (CCD) was also done. The analysis of variance (ANOVA) was used to test the adequacy of the model developed. The statistical significance of the models developed and each term in the regression equation were examined using the sequential F-test, lack-of-fit test and other adequacy measures. To validate the regression model, selected goodness of fit statistics, namely; coefficient of determination (R^2), correlation coefficient (r), Adjusted Coefficient of Determination (R^{-2}) and error sum of square (SSE) were employed. To validate the suitability of the quadratic model in analyzing the experimental data, the sequential model sum of squares was calculated for the response variable. The predictive model generated was then used to express the relationship between the relevant variables using a computer-based method.

The completed experimental design layout in Table 2 shows a 20-trial experimental design and all the experiments were carried out randomly to minimize the effect of unexplained variability in the observed responses due to extraneous factors.

Table 2 - Completed Design layout

Run	Type	Factor 1 No. of Passengers (Nil)	Factor 2 Car Speed (m/s)	Factor 3 Surface Inclination (degree)	Response 1 Distance (m)
1	Center	3.00	17.50	3.50	5.00
2	Center	3.00	17.50	3.50	10.00
3	Center	3.00	17.50	3.50	5.00
4	Center	3.00	17.50	3.50	5.00
5	Center	3.00	17.50	3.50	5.00
6	Center	3.00	17.50	3.50	5.00
7	Axial	3.00	38.52	3.50	10.00
8	Axial	0.36	17.50	3.50	20.00
9	Axial	6.36	17.50	3.50	20.00
10	Axial	3.00	3.52	3.50	12.50
11	Axial	3.00	17.50	9.39	15.00
12	Axial	3.00	17.50	2.39	20.00
13	Fact	5.00	5.00	7.00	20.00
14	Fact	1.00	5.00	0.00	20.00
15	Fact	1.00	5.00	7.00	5.00
16	Fact	1.00	30.00	0.00	20.00
17	Fact	5.00	30.00	7.00	17.00
18	Fact	1.00	30.00	7.00	18.00
19	Fact	5.00	5.00	0.00	25.00
20	Fact	5.00	30.00	0.00	5.00

Analysis of Experiment:

A commercial statistical analysis software DESIGN-EXPERT was employed for design and analysis of the experiment. In DESIGN-EXPERT environment, RSM is used to find a combination of factors which gives the optimal response. The experimental results were analyzed with Analysis Of Variance (ANOVA), which is used for identifying the factors significantly affecting the performance measures. The results were then fitted to the following second order polynomial equation to predict the optimum speed bump location conditions:

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_{ii} X_i^2 + \sum_{i=1} \sum_{j=i+1} \beta_{ij} X_i X_j + \varepsilon \qquad (2)$$

Where, Y represents the response variable, β_0 is the intercept; β_i and β_{ii} are the first and second order quadratic model coefficients for the variables respectively. Also, β_{ij} is the linear model coefficient for the interactions between i and j; X_i and X_j are recorded independent process variables and ε is the random error [de Olivera et al. (2016)]. The predictive model generated was then used to express the relationship between the relevant variables using a computer-based method.

III. RESULTS AND DISCUSSION

The results of this study comprise of both field data and the values gotten from processed information using appropriate, designated computer software (Microsoft Excel and Stat Ease Design Expert 7.01). The optimal equation which show the individual effects, and the combine interactions of the selected input variables, namely; number of passengers, car speed (m/s) and surface inclination (degree)) against the measured response variable, namely; distance of bump placement is presented based on actual factors as follows;

The final equation for distance in terms of actual factors is modelled as:

$$\text{Distance} = 26.97165 - 5.51655A - 0.24232B - 5.45167C - 0.18AB + 0.428571AC + 0.085714BC + 1.218833A^2 + 0.011403B^2 + 0.325833C^2 \quad (3)$$

Where;
A is number of passengers
B is car speed (m/s)
C is surface inclination (degree).

ANOVA:

From the result of Table 3, the Model F-value of 39.48 implies the model is significant. There is only a 0.01% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case B, C, AB, AC, BC, A^2, B^2, C^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. The "Lack of Fit F-value" of 0.25 implies the Lack of Fit is not significant relative to the pure error. There is a 92.46% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good as it indicates a model that is significant.

Table 3: ANOVA table for validating model significance towards optimizing distance of bump placement

Response					1	**Distance**
ANOVA for Response Surface Quadratic Model						
Analysis of variance table [Partial sum of squares - Type III]						
Source	**Sum of Squares**	**df**	**Mean Square**	**F Value**	**p-value Prob > F**	
Model	922.9643	9	102.5516	39.48361	< 0.0001	significant
A-No of Passengers	1.171573	1	1.171573	0.45107	0.5170	
B-Car Speed	14.77407	1	14.77407	5.688197	0.0383	
C-Surface Inclination	24.81464	1	24.81464	9.55394	0.0114	
AB	162	1	162	62.37197	< 0.0001	
AC	72	1	72	27.72088	0.0004	
BC	112.5	1	112.5	43.31387	< 0.0001	
A^2	342.54	1	342.54	131.8821	< 0.0001	
B^2	45.75003	1	45.75003	17.61432	0.0018	
C^2	229.5958	1	229.5958	88.39717	< 0.0001	
Residual	25.9732	10	2.59732			
Lack of Fit	5.139871	5	1.027974	0.246714	0.9246	not significant
Pure Error	20.83333	5	4.166667			
Cor Total	948.9375	19				

Reliability test:

To asses the accuracy of prediction and established the suitability of response surface methodology using the quadratic model, a reliability plot of the observed and predicted values of the response variable was obtained. The high coefficient of determination (R^2 = 0.9726) as observed in Fig. 1 was used to established the suitability of response surface methodology in optimizing distance of bump placement.

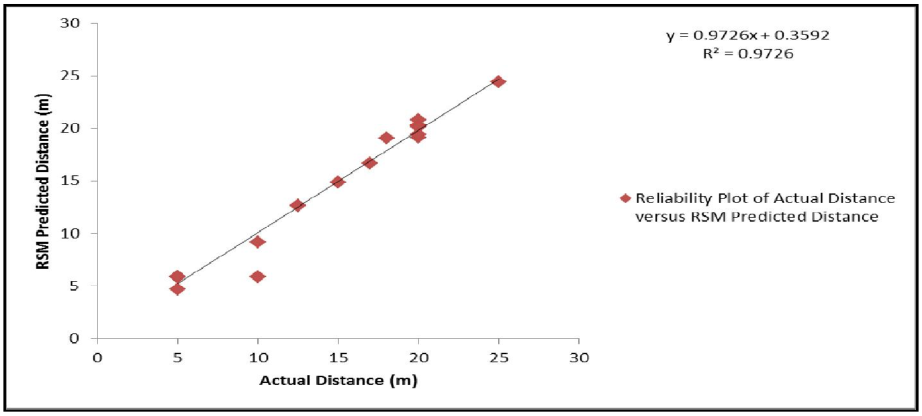


Fig. 1: Reliability plot of actual distance versus predicted

Normal probability plot:

The normal probability plot of studentized residuals was employed to assess the normality of the calculated residuals. The normal probability plot of residuals which is the number of standard deviation of actual values based on the predicted values was employed to ascertain if the residuals (observed – predicted) follows a normal distribution. It is the most significant assumption for checking the sufficiency of a statistical model. Results of Fig. 2 revealed that the computed residuals are approximately normally distributed an indication that the model developed is satisfactory and the data employed are devoid of possible outliers.

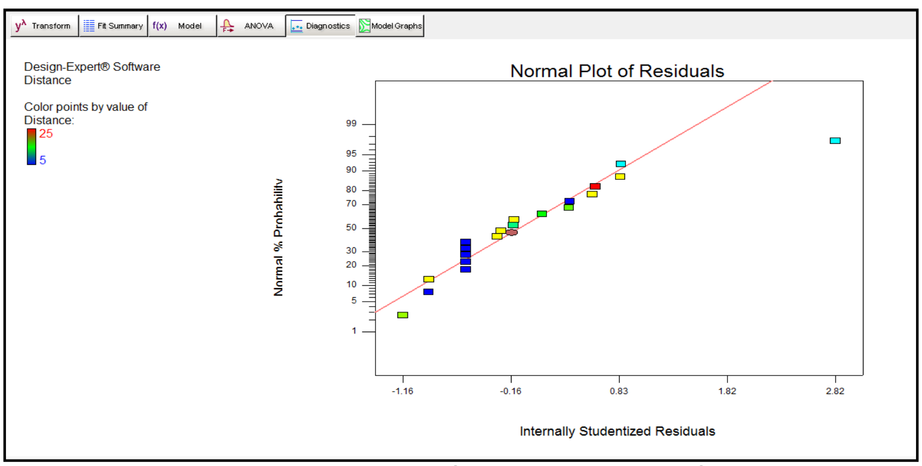


Fig. 2: Normal probability plot of studentized residuals for distance

Model validity:

Goodness of fit statistics:

To validate the adequacy of the quadratic model based on its ability to optimize distance of bump placement, the goodness of fit statistics was employed. Based on the calculated sequential model sum of square, the highest order polynomial where the additional terms are significant and the model is not aliased was selected as the best fit. The goodness of fit of the economic models or robustness were determined from the R-square values which range from 0.92 to 0.97 (See regression models statistical values in Fig. 2). The model's validity was also carried out.

Table 4: GOF for validating model significance towards optimizing distance

Std. Dev.	1.61162		R-Squared	0.972629
Mean	13.125		Adj R-Squared	0.947995
C.V. %	12.27901		Pred R-Squared	0.924015
PRESS	72.1054		Adeq Precision	17.35866
The "Pred R-Squared" of 0.924015 is in reasonable agreement with the "Adj R-Squared" of 0.947995				

From the result of Table 4, it was observed that the "Predicted R-Squared" value of 0.924015 is in reasonable agreement with the "Adj R-Squared" value of 0.947995. Adequate precision measures the signal to noise ratio. A ratio greater than 4 is desirable. The computaed ratio of 17.35866 as observed in Table 4 indicates an adequate signal. This model can be used to navigate the design space and adequately optimize distance of bump placement.

Analysis of the model standard error was employed to assess the suitability of response surface methodology using the quadratic model to optimize the optimum distance of bump placement.

The quadratic polynomial model was suggested while the cubic polynomial model was aliased hence, the quadratic polynomial model was selected since it possesses the lowest predicted error sum of square value of 72.1054, lowest standard deviation of 1.61161, highest adjusted R-square value of 0.947995 and predicted R-square value of 0.924015 with relatively high coefficient of determination of 0.972629.

Standard Error:

From the results of Table 5, it was observed that the model possess a low standard error ranging from 0.271 for the individual terms, 0.353 for the combine effects and 0.263 for the quadratic terms. Standard errors should be similar within type of coefficient; smaller is better. The error values were also observed to be less than the model basic standard deviation of 1.0 which suggests that response surface methodology was ideal for the optimization process.

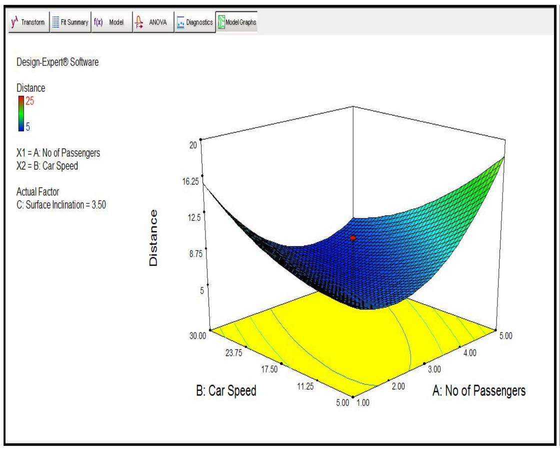
Table 5: Result of computed standard errors

				Power at 5% alpha level for effect of		
Term	StdErr**	VIF	Ri-Squared	0.5 Std. Dev.	1 Std. Dev.	2 Std. Dev.
A	0.270598	1	0	13.3 %	38.6 %	91.4 %
B	0.270598	1	0	13.3 %	38.6 %	91.4 %
C	0.270598	1	0	13.3 %	38.6 %	91.4 %
AB	0.353553	1	0	9.8 %	24.9 %	72.2 %
AC	0.353553	1	0	9.8 %	24.9 %	72.2 %
BC	0.353553	1	0	9.8 %	24.9 %	72.2 %
A^2	0.26342	1.018265	0.017938	40.4 %	92.7 %	99.9 %
B^2	0.26342	1.018265	0.017938	40.4 %	92.7 %	99.9 %
C^2	0.26342	1.018265	0.017938	40.4 %	92.7 %	99.9 %
**Basis Std. Dev. = 1.0						

Variance inflation factor (VIF) of approximately 1.0 as observed in Table 5 was good since ideal VIF is 1.0. VIF's above 10 are cause for alarm, indicating coefficients are poorly estimated due to multicollinearity. In addition, the Ri-squared value was observed to be between 0.0000 to 0.017938 which is good.

3D surface plot:

To study the effects of combine input variables on the response variable (distance), 3D surface plot was employed. The 3D surface plot as observed in Fig. 4 shows the relationship between the input variables (car speed and number of passengers) and the response variables (distance). It is a 3 dimensional surface plot which was employed to give a clearer concept of the response surface. The colour of the surface was observed to be dark towards car speed. The implication is that; car speed has the greatest influence on the distance of bump placement than the number of passengers. This findings is in-line with the outcome of the analysis of variance presented in Table 3 which shows that car speed and surface inclination are more significant than number of passengers in determining the optimum distance of bump placement with surface inclination more significant than car speed as observed in Fig.5. The colour of the surface was observed to be dark towards surface inclination and car speed in Fig.5 which implies that; both surface inclination and car speed have significant influence on the distance of bump placement.



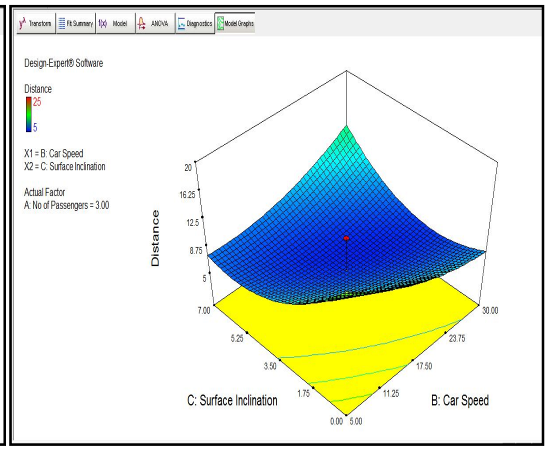


Fig 4: Effect of car speed and number of passenger on distance

Fig 5: Effect of surface inclination and car speed on distance

Optimization of Results:

Numerical optimization was performed to ascertain the desirability of the overall model. The objective of numerical optimization was to determine the optimum number of passengers, optimum car speed and optimum surface inclination that will significantly optimize the distance of bump placement. The interphase of the numerical optimization showing the objective function is shown in Fig.6.

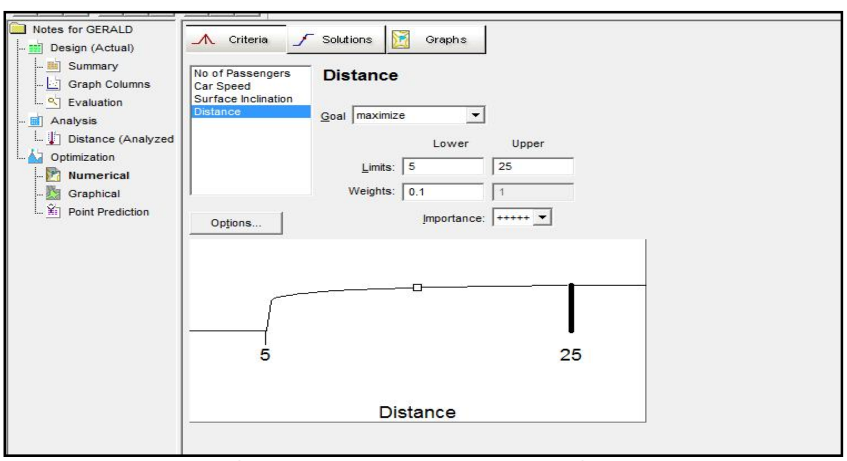


Fig. 6: Interphase of numerical optimization model for optimizing distance

The optimization objective was to optimize the distance of bump placement. The relative importance was set at the optimum value of 5.0 and the lower and upper boundary conditions were set at 0.1 and 1.0 respectively. The final solution of the numerical optimization is presented in Table 6.

Table 6: Optimal solutions of numerical optimization

Number	No of Passengers	Car Speed (m/s)	Surface Inclination (degree)	Distance	Desirability	
1	5	30	7	16.6569	0.9809	Selected
2	4.98	30	7	16.5847	0.9798	
3	5	29.79	7	16.6281	0.9791	
4	4.96	30	7	16.4740	0.9781	
5	5	30	6.9	16.2616	0.9765	
6	5	30	6.87	16.1687	0.9755	
7	4.91	30	7	16.2995	0.9753	
8	4.88	30	7	16.1626	0.9730	
9	5	30	6.58	15.0923	0.9629	
10	4.69	30	7	15.4449	0.9602	
11	5	27.22	7	16.3506	0.9555	
12	4.56	30	7	15.0087	0.9514	
13	5	30	6.15	13.6270	0.9437	
14	5	25.1	7	16.2335	0.9349	

From the results of Table 6, it was observed that for Number of passengers (5), Car speed (30m/s) and Surface inclination (7^0), the optimum bump distance is 16.6569m. This solution was selected by design expert as the optimal solution with a desirability value of 98.09%.

The ramp solution which is the graphical presentation of the optimal solution is presented in Fig.7 while the desirability bar graph which shows the accuracy with which the model is able to predict the values of the selected input variables and the corresponding response variable is presented in Fig.8.

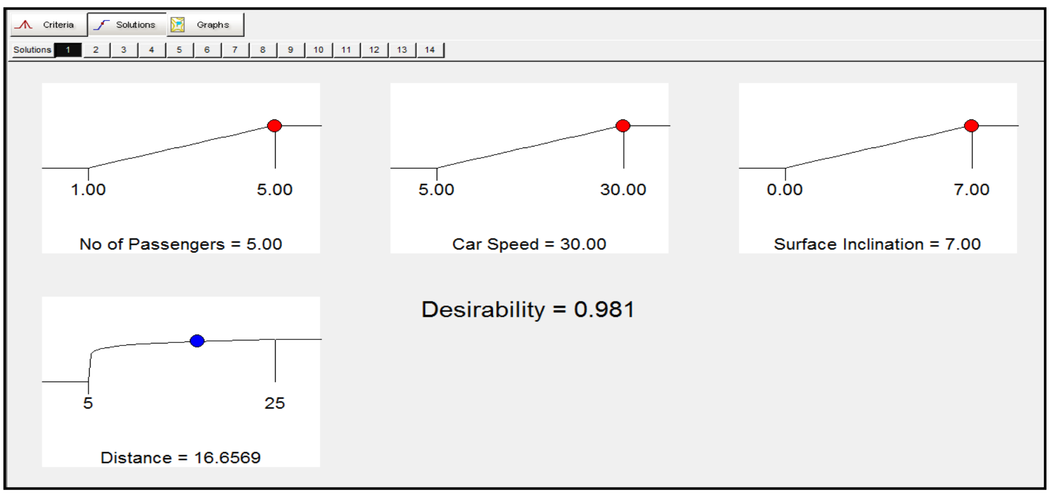


Fig. 7: Ramp solution of numerical optimization

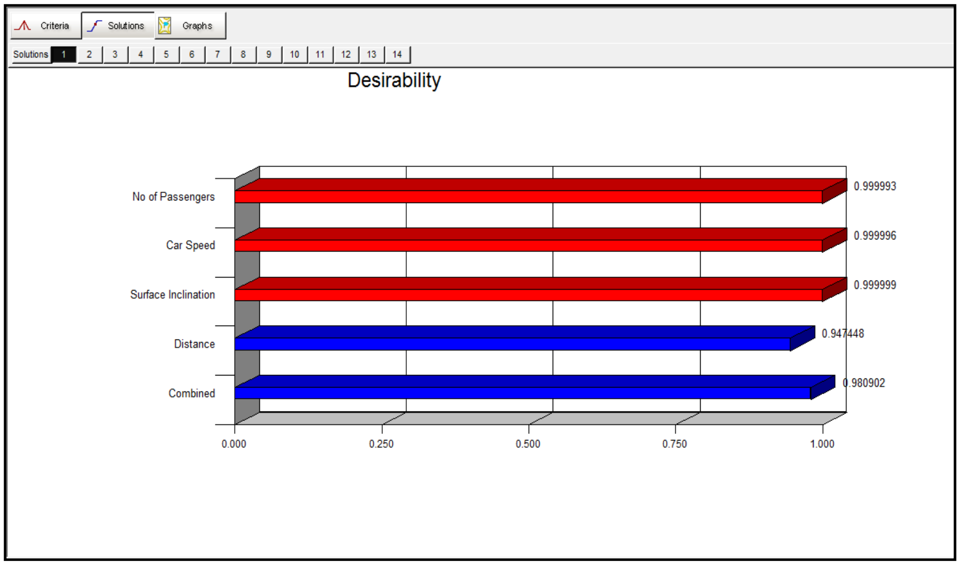


Fig. 8: Desirability bar graph

IV. CONCLUSION AND RECOMMENDATIONS

A. Conclusion

1. The experimental results show that the proposed mathematical model explained the performance indicators within the ranges of the critical factors that are being examined effectively.

2. It was concluded that the best location for setting up the speed bump is at 16.66m prior to the stop point in order to achieve the minimum speed at the convenient stop at the stop point.

3. The results of the analysis showed that, the optimum point within the experimental range investigated, is obtained when the speed is maximum i.e. 30 m/s.

4. Based on the results of the computed design, the percentage contributions of these factors on the response is specified using Classical DOE technique.

B. Recommendation

1. It is recommended that this study be extended to other roads with speed bumps in Delta State of Nigeria so as to standardize them as well as in other parts of the country.
2. As the current operating condition is normally far from the true optimum response, for the future studies, experimenters need to move from the current operating conditions to the optimum region in the most efficient way using the minimum number of experiments.
3. In addition, it is recommended this study be extended to other DOE software.

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