Original Research

Application on Concurrent Product Design and Process Planning for A bicycle Design

Abbas Al-Refaie

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* Corresponding Author, abbas.alrefai@edu.ju.jo
Department of Industrial Engineering, University of Jordan, Amman, Jordan

Abstract

A high degree of uncertainty is incurred during the early product design and process planning stages of a bicycle. Consequently, this research presents an optimization procedure for the design of critical components of a bicycle frame and planning of their corresponding processes using simulation and fuzzy goal programming (FGP). For this frame, the reliability, dependability, mass, and fatigue factor were the main quality responses. Initially, the critical bicycle's frame components with their corresponding design parameters and tolerances were identified via technical knowledge. Designed experimentation based on the Taguchi's array was conducted by simulation with twenty replicates for various combinations of design parameters and tolerances of the key frame components. Then, satisfactory regression models were formulated to relate each quality response with design parameters and tolerances and then inserted in the optimization model. The design parameters and tolerances and processes' means and tolerances were expressed in terms of fuzzy membership functions and their relevant goals and constraints were included in the optimization model. Finally, the objective functions were minimizing the negative and positive deviation from desired goals and maximizing process capability indices. Results showed that the FGP optimization procedure effectively achieved the desired targets of the bicycle's quality responses and process capability indices. In conclusion, the proposed procedure can be used for optimal concurrent product and process design in a wide range of industrial applications.

Keywords - Fuzzy goal programming; Optimization, Product design; Process design; Simulation

INTRODUCTION

Today's sharp competition has urged concurrent product design and process planning to improve product functionality and enhance process performance. Product design aims at determining the design's parameter (target value) and tolerance (acceptable limits) of critical product components while considering customer satisfaction and functional requirements. Product quality is then defined as the degree of which desired targets of quality characteristics are achieved [1]. On the other hand, process planning determines the combination of optimal process means and tolerances that guarantee the processing feasibility. In practice, process engineers should determine processes' means and tolerances that guarantee acceptable design targets and tolerances in order to achieve product quality and process performance. Therefore, an approach for a simultaneous product design and process planning is required during the early design stage prior to the real product.

Recently, concurrent product design and process planning received significant research attention. For example, Mcadams and Wood [2] dealt with tolerance design issues via adjust single performance parameters of product that affect the customers' needs on heavy duty manual stapler. Jeang and Chang [3] studied tolerance design utilizing orthogonal array, computer simulation and statistical analysis. The parameters and tolerances were obtained by minimizing quality loss and the tolerance cost. Jeang [4] conducted simultaneous optimization of parameters and tolerances of an electronic circuit design via response surface methodology and computer simulation. The model's objectives were quality loss, tolerance cost, and failure cost. Singh *et al*. [5] determined the optimal tolerance synthesis of mechanical assemblies with alternative manufacturing processes using genetic algorithm-based solution. Agyapong-Kodua *et al.* [6] proposed an integrated product–process design methodology for cost-effective product realization. Jeang [7] proposed optimal product design and process planning by minimizing the total of mean cost, tolerance cost, quality loss, inspection and failure. Jeang [8] introduced optimization model for concurrent process mean, process tolerance and product specification utilizing Box-Behnken experimental matrix, Monte Carlo simulation and response surface methodology. Jeang and Lin [9] determined product and process parameters concurrently for combined quality and cost. The objective functions of the optimization model consisted of mean cost, tolerance cost, quality loss and failure cost. Chen and Chou [10] adopted the Burr distribution to determine the optimum process mean, standard deviation, and specification limits under non-normality. Al-Refaie *et al.* [11] proposed a mathematical model for optimal parameters and tolerances in concurrent product and process design using simulation and fuzzy goal programming. This research considers the application of concurrent optimization of design parameters and processes' means and tolerances for the critical component of a bicycle frame, in which a high degree of uncertainty is involved in the early design stage due to fuzzy customer preferences and unstable process parameters [12-14].

The fuzzy goal programming (FGP) has been reported as an effective technique for optimizing process performance under uncertainty in a wide range of business applications [15-17]. Consequently, this research uses the FGP modeling for concurrent product design and process planning for the component of bicycle frame. In other words, this research aims to determine optimal design parameters and tolerances with the corresponding processes' means and tolerances for the critical components of bicycle's frame that guarantee achieving customer preferences on bicycle's quality responses and maximizing process capability indices. The remaining of this paper including the introduction is outlined in the following sequence. Section two presents bicycle design and analysis. Section three conducts optimization of bicycle design. Section four presents optimization results. Section 5 summarizes conclusions.

OPTIMIZATION PROCEDURE

The optimization procedure for a bicycle's components design and process planning is depicted in Fig. 1.

I. Defining quality responses and controllable factors

Four quality responses are considered critical in the design of the bicycle frame, which are identified based on customer preferences and frame functionality, including:

(i) Reliability, which indicates that the frame can withstand the applied loads without failure; the maximum stress applied to the frame must be lower than the frame's yields limit taking into consideration load variation and an appropriate safety factor. Reliability is defined here as the probability the maximum stress being less than 3.5×107Pa.

(ii) Dependability, where the permanent deformation of the bicycle should be kept minimal; excessive deformation changes the structure shape. Dependability is calculated as the probability deformation being less than 0.00014 mm.

(iii) Mass of the frame should be as light as possible to accommodate different users with different strengths and needs and provide them with a better experience, where a light frame is more preferable.

(iv) Fatigue factor of safety, which is estimated by the probability of having a safety factor larger than two.

The specification limits of the four quality characteristics are listed in Table 1.

TABLE 1. SPECIFICATION LIMITS OF BICYCLE QUALITY CHARACTERISTICS

Quality Characteristics	LSL	Target	USL
y_1 : Reliability	0.98	-	1.00
y_2 : Dependability	0.98	-	1.00
y_3 : Mass	-	-	1.2
y_4 : Fatigue Factor	2	-	-

II. CONSTRUCTING BICYCLE FRAME DESIGN

The frame is the main component of a bicycle onto which wheels and other components are fitted. The most common frame design consists of two triangles; a main triangle and a paired rear triangle. Frames are required to be strong, stiff and light. Fig.2 shows a schematic sketch of a bicycle frame with and without fork. In this research, the analysis will be conducted on the frame without the fork and the interface of assembly between the fork and the frame is considered as a fixed support [18-19].

The bicycle frame is shown in Fig. 3, which is composed of critical components including forks, head tube, top tube, down tube, seat tube, seat stays,
chain stays, bottom brackets shell. Several material types can be used to build the frame; such as, Steels, Titanium, and Aluminum alloys. In this research, a high strength to weight ratio and affordable design aluminum alloy was chosen in building the frame, which is the Aluminum Alloy 6061-T6 of the mechanical properties shown in Fig. 4. This

frame is designed to carry a load up to 130 kg, which is designed to accommodate two persons. The seat is assumed to handle 54 % of the weight (686.7N), the handle bar and the paddles are each assumed to handle 23% of the weight (294.3N). Fig. 5 displays the forces distribution.

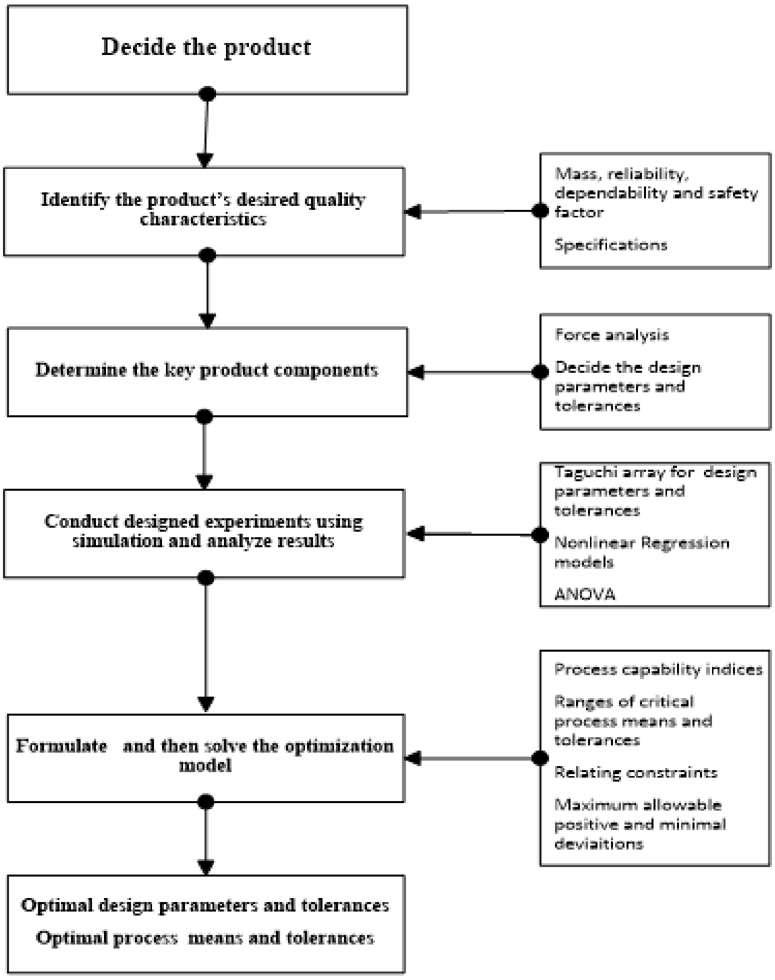


FIG. 1. THE OPTIMIZATION PROCEDURE FOR BICYCLE DESIGN AND PROCESS PLANNING.

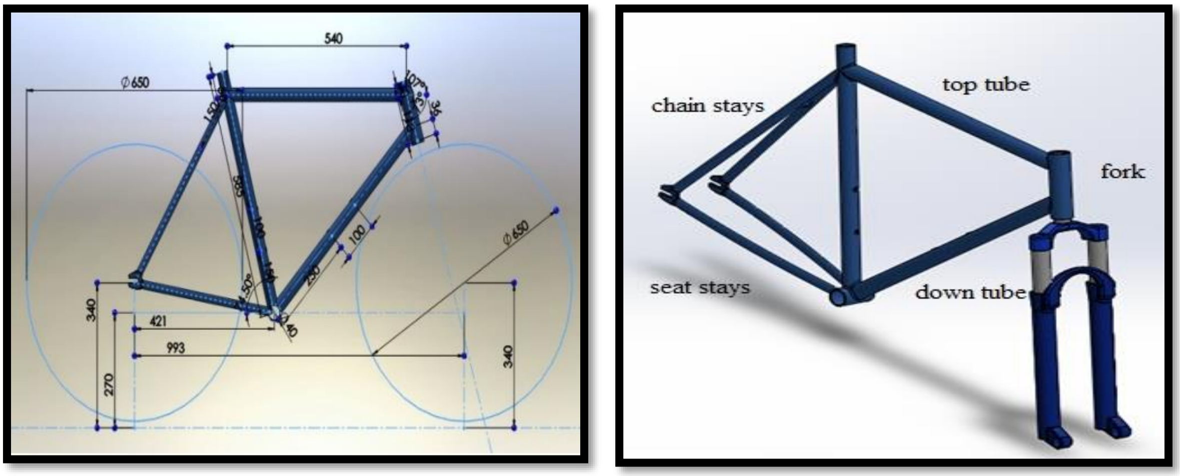


FIG. 2. A SCHEMATIC SKETCH OF A BICYCLE FRAME.

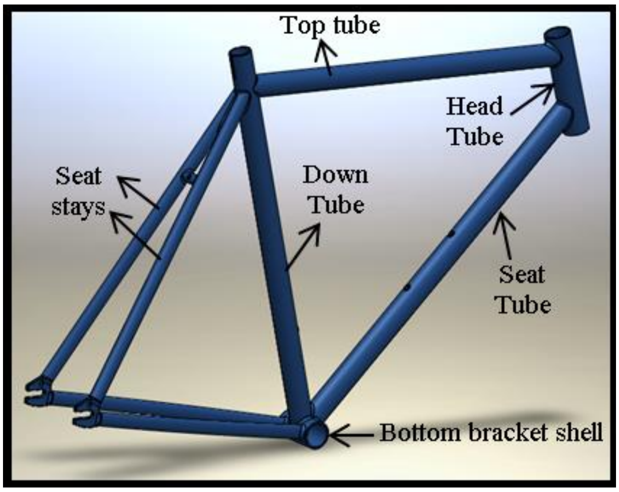
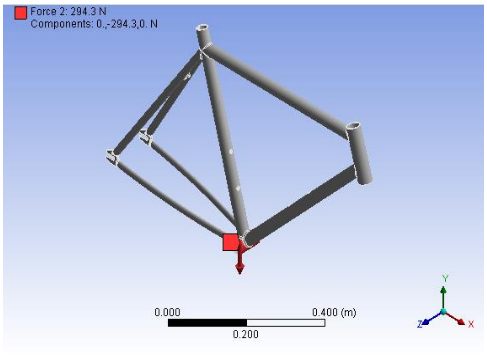


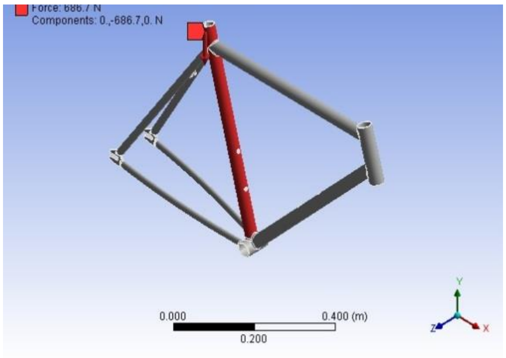
FIG. 3. FINAL DESIGN OF BICYCLE FRAME AND ITS COMPONENTS.

Young's Modulus	7.1e+010 Pa
Poisson's Ratio	0.33
Density	2770. kg/m³
Thermal Expansion	2.3e-005 1/°C
Alternating Stress	
Tensile Yield Strength	2.8e+008 Pa
Compressive Yield Strength	2.8e+008 Pa
Tensile Ultimate Strength	3.1e+008 Pa
Compressive Ultimate Strength	0. Pa
Thermal Conductivity	
Specific Heat	875. J/kg·°C
Relative Permeability	1.
Resistivity	5.7e-008 Ohm·m

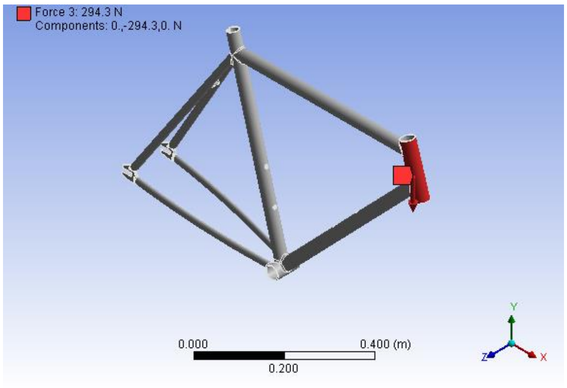
FIG 4. MATERIAL PROPERTIES OF ALUMINUM ALLOY.



Force on seat



Force on paddles



Force on handle bar

FIG. 5. ILLUSTRATION OF LOADS ON THE FRAME.

The means and tolerances of the critical controllable factors that are believed to affect the reliability, dependability, mass, and fatigue resistance of the bicycle frame are given in Table 2. The block diagram for bicycle frame design is then shown in Fig. 6.

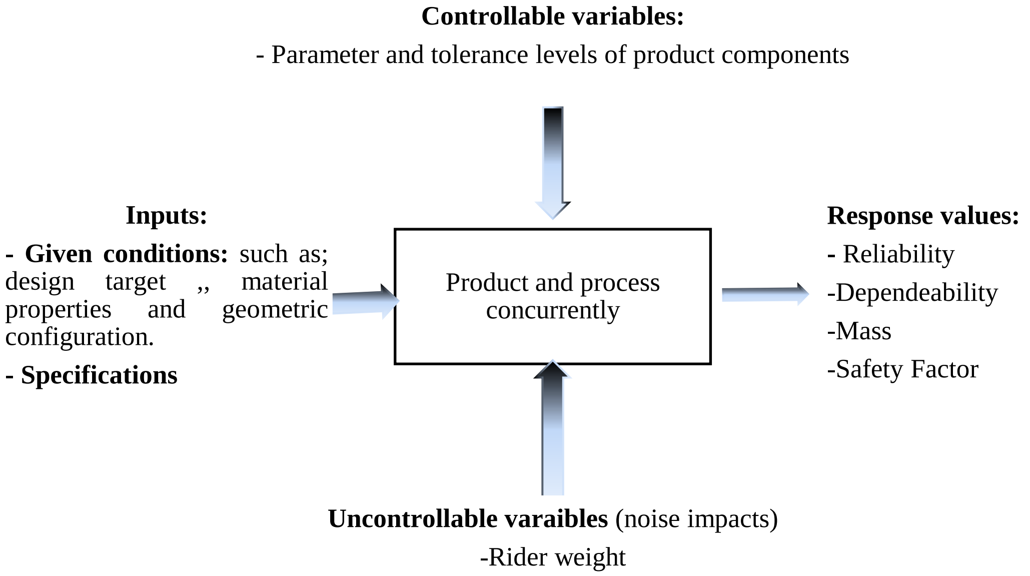


FIG. 6. BLOCK DIAGRAM FOR BICYCLE SYSTEM.

III. Conducting Experimental Design

To conduct experimental design, the design means and tolerances are assigned at three physical level values as shown in Table 3. The Taguchi's L_{54} array shown in Table 4 enables studying up to 25 factors, one at two levels and the others at three levels by conducting only 54 experiment. A static analysis was performed on the frame and then a central composite design was used to perform a probabilistic analysis that takes into account the tubes' diameters and tolerances. The jth tube diameter is assumed to have a normal distribution with a mean (μ_j) equal to the experiment level diameter and standard deviation (σ_j) equal to three times tolerance (t_j) of the experiment level. Fig. 7 shows snap shots from the statistical analysis that done on the frame. For each combination of controllable factors (experiment), simulation was repeated twenty times to obtain twenty replicates for each quality response. Then, the averages of mass and the best fit probability distribution of stress, deformation, and fatigue safety factor were calculated.

Utilizing the probability distributions at each experiment, the reliability, dependability and probability of fatigue safety factor greater than two were determined. At experiment No.10, for illustration, the average mass was calculated and found to be 1.044268 kg. Moreover, the reliability was estimated as follows:

- Fit the distribution for the maximum stress.
- Estimate the reliability as the probability that the maximum stress is less than 3.5×10^7 Pa.

For example, the probability distribution of the stress at experiment No.10 was fitted, as shown in Fig. 8, by the largest extreme value distribution of location equals to 2.79892×10^7 and scale of 2.76725×10^6. Then, reliability was then calculated and found to be 92.37%. Furthermore, the dependability was calculated by the following steps:

- Identify the distribution for the maximum stress.
- Calculate the dependability as the probability that the maximum deformation is less than 0.00014m.

At experiment No. 10, for example, the best distribution fit of the maximum deformation, as depicted in Fig. 8, is the lognormal distribution, the p-value is found to be 0.795, which indicates acceptable fit. The distribution location and scale were 9.01374 and 0.02533, respectively. The dependability was then calculated and found to be 100%.

Finally, the adequate probability distribution of the fatigue safety factor being larger than two for each experiment was estimated by:

- *Identifying the distribution for the fatigue safety factor for each experiment.*
- *Calculating the probability that the minimum fatigue safety factor is larger than two.*

At experiment 10, for illustration, the distribution of the minimum fatigue safety factor was satisfactorily modeled, as displayed in Fig. 8, by the Weibull distribution of shape and scale parameters of 10.1325 and 2.97, respectively. The probability that the minimum fatigue safety factor is larger than two was calculated and found to be 98.2%. Finally, the best fit probability distributions of reliability, dependability, and fatigue safety factor for all experiments are listed in Tables 5 to 7, respectively.

IV. DEVELOPING MULTIPLE REGRESSION ANALYSIS

Multiple regression models were formulated to depict the relationships between the measured values of each of the four quality responses and the controllable factors followed by analysis of variance (ANOVA). For mass (y_1), the multiple regression model is expressed as:

$$\text{Mass}\ (y_1) = 0.03998\mu_1 - 0.03989\mu_2 + 0.05048\mu_3 - 0.02536\mu_4 + 0.02406\mu_5 - 0.03040\mu_6 + 0.01774\mu_7 - 0.01978\mu_8 - 0.021\sigma_1 + 0.152\sigma_2 - 0.034\sigma_3 + 0.051\sigma_4 - 0.100\sigma_5 + 0.182\sigma_6 + 0.149\sigma_7 - 0.104\sigma_8$$

The ANOVA analysis for mass is displayed in Table 8, where the regression model is found acceptable (p value = 0.00). Similarly, the regression model for reliability (y_2) and dependability (y_3) values are estimated and can be expressed respectively as:

$$\text{Reliability}\ (y_2) = 0.0226\mu_1 - 0.0550\mu_2 + 0.0523\mu_3 - 0.0623\mu_4 + 0.1016\mu_5 + 0.0856\mu_6 - 0.0785\mu_7 - 0.0108\mu_8 + 0.272\sigma_2 + 0.452\sigma_4 + 0.198\sigma_5 - 0.36\sigma_6 + 0.852\sigma_7 - 0.117\sigma_8$$

and

$$\text{Dependability}\ (y_3) = 3.95\mu_1 - 2.917\mu_2 - 1.72\mu_3 + 2.204\mu_4 + 0.0305\mu_5 - 1.301\mu_6 - 1.547\mu_7 - 0.0008\mu_8 - 0.372\sigma_1 + 0.204\sigma_2 + 0.131\sigma_3 + 0.182\sigma_4 - 0.348\sigma_5 + 1.623\sigma_6 + 0.519\sigma_7 - 0.067\sigma_8 - 0.0609\mu_1^2 + 0.063212\mu_1\mu_2 - 0.0827\mu_1\mu_4 + 0.0362\mu_2\mu_3 + 0.0164\mu_3^2 + 0.0516\mu_6^2 + 0.0432\mu_7^2$$

Finally, the regression model for the fatigue safety factor (y_4) is formulated as:

$$\text{Fatigue}\ (y_4) = -0.962\mu_1 + 0.648\mu_2 - 0.851\mu_3 + 1.449\mu_4 + 0.0637\mu_5 + 0.0116\mu_6 - 0.0023\mu_7 - 0.0166\mu_8 - 0.129\sigma_1 + 0.292\sigma_2 - 0.078\sigma_3 + 0.288\sigma_4 + 0.291\sigma_5 - 0.097\sigma_6 + 0.160\sigma_7 + 0.142\sigma_8 + 0.0164\mu_1\mu_2 - 0.0053\mu_2\mu_3 + 0.0373\mu_1\mu_3 - 0.0186\mu_1\mu_4 - 0.0402\mu_2\mu_4 - 0.0012\mu_3\mu_4$$

The ANOVA results for y_1 to y_4 are displayed in Table 8, where it is found that the regression models are reliable ($R_{\text{-sq. (adj)}}$ > 92.00%) for explaining the relationships between each quality response and the controllable factors.

TABLE 2. CRITICAL CONTROLLABLE FACTORS WITH THEIR TOLERANCES.

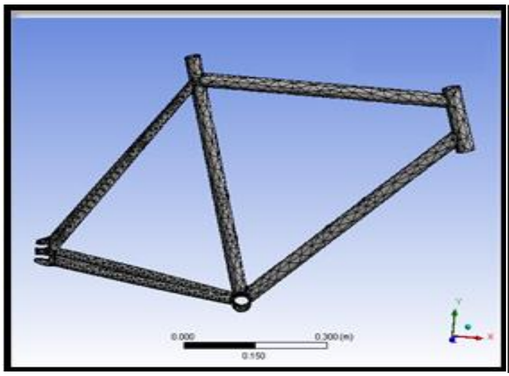
Critical dimension (Mean)	t	σ
Mean of outer diameter of the top tube (μ_1)	t_1	σ_1
Mean of inner diameter of the top tube (μ_2)	t_2	σ_2
Mean of outer diameter of the down tube (μ_3)	t_3	σ_3
Mean of inner diameter of the down tube (μ_4)	t_4	σ_4
Mean of outer diameter of seat stay ((μ_5)	t_5	σ_5
Mean of inner diameter of seat stay (μ_6)	t_6	σ_6
Mean of outer diameter of chain stay (μ_7)	t_7	σ_7
Mean of inner diameter of chain stay (μ_8)	t_8	σ_8

TABLE 3. PHYSICAL LEVEL VALUES OF DESIGN MEANS AND TOLERANCES.

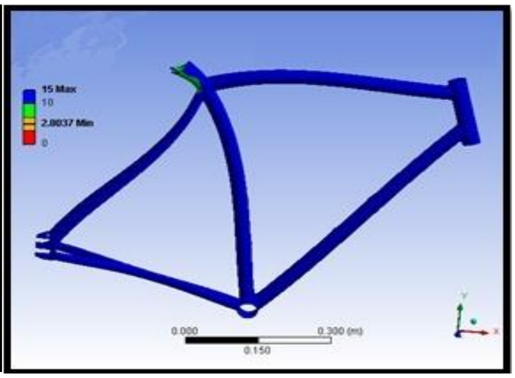
Parameter	***level***			***Parameter***	***level***		
	1	*2*	*3*		*1*	*2*	*3*
μ_1	*30*	*32*	*34*	t_1	*0.34*	*0.64*	*0.90*
μ_2	*25*	*27*	*29*	t_2	*0.29*	*0.54*	*0.75*
μ_3	*31*	*33*	*35*	t_3	*0.35*	*0.66*	*0.93*
μ_4	*26*	*28*	*30*	t_4	*0.31*	*0.56*	*0.78*
μ_5	*17*	*19*	*21*	t_5	*0.21*	*0.38*	*0.51*
μ_6	*12*	*14*	*16*	t_6	*0.16*	*0.28*	*0.36*
μ_7	*18*	*20*	*22*	t_7	*0.22*	*0.40*	*0.54*
μ_8	*13*	*15*	*17*	t_8	*0.17*	*0.30*	*0.39*

TABLE 4. THE LAYOUT OF THE L_{54} ARRAY.

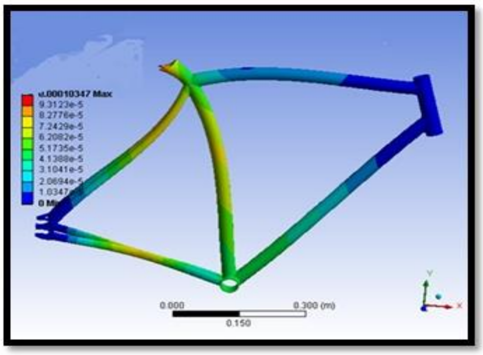
Exp.	Factor level																									
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
3	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
4	1	1	2	2	2	2	2	2	1	1	1	1	1	1	2	3	2	3	2	3	2	3	2	3	2	3
5	1	1	2	2	2	2	2	2	2	2	2	2	2	2	3	1	3	1	3	1	3	1	3	1	3	1
6	1	1	2	2	2	2	2	2	3	3	3	3	3	3	1	2	1	2	1	2	1	2	1	2	1	2
7	1	1	3	3	3	3	3	3	1	1	1	1	1	1	3	2	3	2	3	2	3	2	3	2	3	2
8	1	1	3	3	3	3	3	3	2	2	2	2	2	2	1	3	1	3	1	3	1	3	1	3	1	3
9	1	1	3	3	3	3	3	3	3	3	3	3	3	3	2	1	2	1	2	1	2	1	2	1	2	1
10	1	2	1	1	2	2	3	3	1	1	2	2	3	3	1	1	1	1	2	3	2	3	3	2	3	2
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
49	2	3	2	1	3	1	2	3	1	3	2	3	1	2	2	3	1	1	3	2	1	1	2	3	3	2
50	2	3	2	1	3	1	2	3	2	1	3	1	2	3	3	1	2	2	1	3	2	2	3	1	1	3
51	2	3	2	1	3	1	2	3	3	2	1	2	3	1	1	2	3	3	2	1	3	3	1	2	2	1
52	2	3	3	2	1	2	3	1	1	3	2	3	1	2	3	2	2	3	1	1	2	3	3	2	1	1
53	2	3	3	2	1	2	3	1	2	1	3	1	2	3	1	3	3	1	2	2	3	1	1	3	2	2
54	2	3	3	2	1	2	3	1	3	2	1	2	3	1	2	1	1	2	3	3	1	2	2	1	3	3



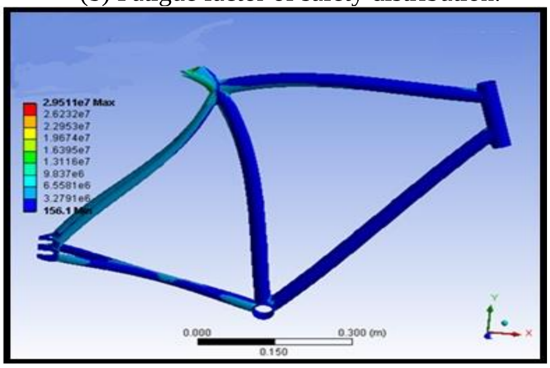
(a) Finite element distribution (mesh).



(b) Fatigue factor of safety distribution.

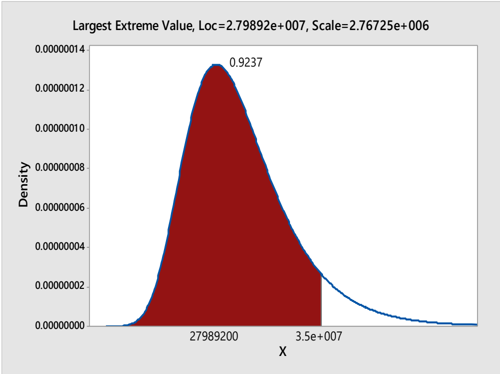


(c) Deformation distribution.

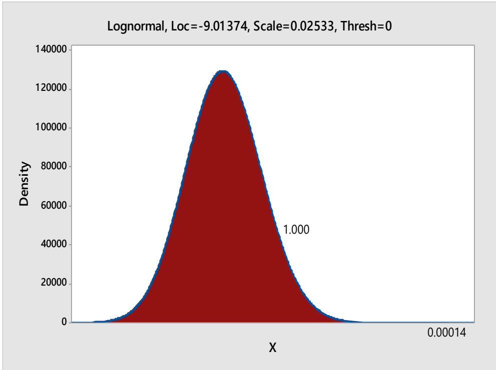


(d) Stress distribution.

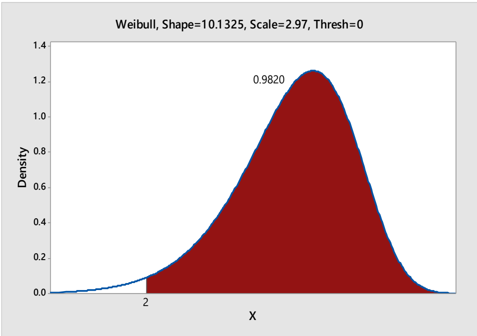
FIG. 7. SNAPSHOTS FROM THE STATIC ANALYSIS ON THE BICYCLE FRAME.



(a) Maximum stress.



(b) Maximum deformation.



(c) Fatigue safety factor.

FIG. 8. THE FITTED PROBABILITY DISTRIBUTION AT EXPERIMENT 10.

TABLE 5. STATISTICAL ANALYSIS RESULTS FOR FRAME'S RELIABILITY AND MASS.

No.	ess distribution	*p* value	Reliability at 8 safety factor	rameters	Average mass
1	Normal	0.410	0.1468	Mean= 4.16451E+07 STD deviation= 6.3272E+06	1.22860
2	Log logistic	0.235	0.2787	Location= 17.46962 Scale= 0.10388	1.19770
3	Lognormal	0.334	0.1382	Location= 17.58217 Scale= 0.19415	1.15864
4	Normal	0.212	0.974	Location= 2.87322E+07 Scale= 3.22424E+06	1.22132
5	Weibull	>0.250	0.9945	Shape= 8.58467 Scale= 2.88822E+07	1.19034
6	Weibull	0.08	0.3625	Location= 1.45191 Scale= 6.06447E+07	1.04920
7	Largest Extreme Value	0.11	0.7093	Location= 3.92849E+07 Scale= 2.90251E+07	1.13318
8	Largest Extreme Value	0.21	0.3447	Location= 3.57674E+07 Scale= 1.21953E+07	1.10685
9	2 parameter exponential	0.178	0.8084	Scale= 2.02565E+07 Threshold= 1.9068E+07	1.10155
10	Largest extreme value	0.024	0.9237	Location= 2.79892E+07 Scale= 2.76725E+06	1.22855
⋮	⋮	⋮	⋮	⋮	⋮
11	Gamma	0.065	0.8581	Shape= 45.60857 Scale= 6.61995E+05	1.19833
30	Smallest extreme value	0.250	0.8765	Location= 3.31912E+07 Scale= 2.45110E+06	1.20629
31	Normal	0.506	1	Mean= 2.37883E+07 STD deviation= 2.32982E+06	1.13663
32	Normal	0.801	1	Mean= 4.1660E+07 STD deviation= 2.34736E+06	1.10639
33	Largest extreme value	0.168	0.9801	Location =2.47121e+007, Scale=2.63152e+006	1.07042
34	Weibull	0.09	0.247	Shape= 4.26548 scale= 4.69795E+07	1.13064
35	3 parameter lognormal	0.808	0.2433	Location 16.15943 Scale=1.43807, threshold=3.3.11683E+07	1.10363
⋮	⋮	⋮	⋮	⋮	⋮
52	Smallest extreme value	0.096	1	Location= 2.42598E+07 Scale= 3.31939E+06	1.28252
53	Weibull	0.092	0.9997	Shape= 5.79677 Scale= 2.44070E+07	1.28395
54	Weibull	0.25	0.9991	Shape= 7.18311, Scale= 2.40193E+07	1.24790

TABLE 6. STATISTICAL ANALYSIS RESULTS FOR FRAME'S DEPENDABILITY.

No.	Deformation distribution	*p* value	Dependability (less than .00014 *m*)	Parameters
1	Weibull	0.01	0.9682	Shape= 6.70590 Scale= 0.00013
2	Largest extreme value	0.214	1	Loc=0.00012, Scale=1e-006
3	log logistic	0.058	0.9658	Location= -8.95894 Scale= 0.02546
4	Weibull	0.11	0.2889	Shape= 8.05907 Scale= 0.00016
5	Largest extreme value	0.31	0.06599	Location= 0.00015 Scale= 0.00001
6	Weibull	0.33	0.2528	Shape= 1.26848 Scale= 0.00037
7	Largest Extreme Value	0.08	0.1024	Shape =1.26848 Scale= 0.00037
8	Weibull	0.09	0.07667	Shape=2.75962, Scale=0.00035,
9	2 Parameter exponential	0.032	0.2485	Scale= 0.00014 Threshold= 0.00013
10	Lognormal	0.795	1	Location =-9.01374 Scale= 0.02533
⁞	⁞	⁞	⁞	⁞
20	Log logistic	0.181	1	Loc=- 9.27223, Scale=0.0076
21	Weibull	>0.250	1	Shape= 71.9397, Scale=9e-005
22	Lognormal	0.644	1	Loc= -9.00758, Scale=0.02831
23	2 Parameter exponential	0.024	0.8647	Scale= 1e-005, Thresh=0.00012
24	Log logistic	0.132	0.7048	Loc=- 8.91045, Scale=0.04204
⁞	⁞	⁞	⁞	⁞
50	Weibull	0.14	0.007783	Shape 1.55050 scale 0.00032
51	2 Parameter exponential	0.051	0.09516	Scale=0.0001, Thresh=0.00013
52	Lognormal	0.973	1	Loc=-9.08705, Scale=0.01604
53	Log logistic	>0.250	1	Loc=-9.08515, Scale=0.01291
54	Lognormal	0.411	1	Loc=-9.07301 Scale=0.0235

TABLE 7. STATISTICAL ANALYSIS RESULTS FOR FRAME'S FATIGUE FACTOR OF SAFETY.

No.	Fatigue distribution	*p* value	Probability fatigue safety factor is larger than 2	Parameters
1	Largest extreme value	>0.250	0.4707	Loc=1.8856, Scale=0.25296
2	logistic	>0.250	0.67	Loc=2.1548, Scale=0.21862
3	lognormal	0.334	0.4101	Loc=0.649, Scale=0.19415
4	Log logistic	0.030	0.9960	Loc=1.0569, Scale=0.0659
5	Largest extreme value	>0.250	1	Loc=2.8852, Scale=0.34297
6	Weibull	0.010	0.5532	Shape=2.281, Scale=2.5166
7	Weibull	0.110	0.5243	Shape=2.33, Scale=2.4127
8	Smallest extreme value	0.070	0.6410	Loc=2.53, Scale=0.65653
9	Largest extreme value	0.220	0.6593	Loc=2.067, Scale=0.9083
10	Weibull	0.065	0.9820	Shape=10.13, Scale=2.97
11	Gamma	0.113	0.9815	Shape=44.846, Scale=0.062
⋮	⋮	⋮	⋮	⋮
20	Largest extreme value	>0.250	1	Loc=4.810, Scale=0.1771
21	Log logistics	0.197	1	Loc=1.57488, Scale=0.031
22	Largest extreme value	>0.250	0.9040	Loc=2.5876, Scale=0.69
23	Smallest extreme value	>0.250	0.9836	Loc=3.613, Scale=0.39299
24	Normal	0.995	0.8747	Mean=2.756, StDev=0.6583
⋮	⋮	⋮	⋮	⋮
50	Smallest extreme value	0.16	0.2611	Loc=1.85138, Scale=0.504
51	Weibull	0.81	0.2578	Shape=3.645, Scale=1.83986
52	Largest extreme value	0.19	1	Loc=3.480, Scale=0.50064
53	Largest extreme value	0.077	1	Loc=3.4456, Scale=0.6257
54	Largest extreme value	0.135	1	Loc=3.7226, Scale=0.6752

Multiple regression models were formulated to depict the relationships between the measured values of each of the four quality responses and the controllable factors followed by analysis of variance (ANOVA). For mass (y_1), the multiple regression model is expressed as:

Mass (y_1)

$$= 0.03998\mu_1 - 0.03989\mu_2 + 0.05048\mu_3 - 0.02536\mu_4 + 0.02406\mu_5 - 0.03040\mu_6 + 0.01774\mu_7 - 0.01978\mu_8 - 0.021\sigma_1 + 0.152\sigma_2 - 0.034\sigma_3 + 0.051\sigma_4 - 0.100\sigma_5 + 0.182\sigma_6 + 0.149\sigma_7 - 0.104\sigma_8$$

The ANOVA analysis for mass is displayed in Table 8, where the regression model is found acceptable (p value = 0.00). Similarly, the regression model for reliability (y_2) and dependability (y_3) values are estimated and can be expressed respectively as:

Reliability (y_2)

$$= 0.0226\mu_1 - 0.0550\mu_2 + 0.0523\mu_3 - 0.0623\mu_4 + 0.1016\mu_5 + 0.0856\mu_6 - 0.0785\mu_7 - 0.0108\mu_8 + 0.272\sigma_2 + 0.452\sigma_4 + 0.198\sigma_5 - 0.36\sigma_6 + 0.852\sigma_7 - 0.117\sigma_8$$

Dependability (y_3)

$$= 3.95\mu_1 - 2.917\mu_2 - 1.72\mu_3 + 2.204\mu_4 + 0.0305\mu_5 - 1.301\mu_6 - 1.547\mu_7 - 0.0008\mu_8 - 0.372\sigma_1 + 0.204\sigma_2 + 0.131\sigma_3 + 0.182\sigma_4 - 0.348\sigma_5 + 1.623\sigma_6 + 0.519\sigma_7 - 0.067\sigma_8 - 0.0609\mu_1^2 + 0.063212\mu_1\mu_2 - 0.0827\mu_1\mu_4 + 0.0362\mu_2\mu_3 + 0.0164\mu_3^2 + 0.0516\mu_6^2 + 0.0432\mu_7^2$$

Finally, the regression model for the fatigue safety factor (y_4) is formulated as:

Fatigue (y_4)

$$= -0.962\mu_1 + 0.648\mu_2 - 0.851\mu_3 + 1.449\mu_4 + 0.0637\mu_5 + 0.0116\mu_6 - 0.0023\mu_7 - 0.0166\mu_8 - 0.129\sigma_1 + 0.292\sigma_2 - 0.078\sigma_3 + 0.288\sigma_4 + 0.291\sigma_5 - 0.097\sigma_6 + 0.160\sigma_7 + 0.142\sigma_8 + 0.0164\mu_1\mu_2 - 0.0053\mu_2\mu_3 + 0.0373\mu_1\mu_3 - 0.0186\mu_1\mu_4 - 0.0402\mu_2\mu_4 - 0.0012\mu_3\mu_4$$

where it is found that the regression models are reliable ($R_{\text{sq. (adj)}} > 92.00\%$) for explaining the relationships between each quality response and the controllable factors.

The ANOVA results for y_1 to y_4 are displayed in Table 8,

TABLE 8. ANOVA RESULTS.

(a) MASS (Y_1).

Source	*df*	*Adj SS*	*Adj MS*	*P-Value*	*Source*	*df*	*Adj SS*	*Adj MS*	*P-Value*
Regression	16	64.8907	4.05567	0.000	σ_3	1	0.0004	0.00039	0.800
μ_1	1	0.2246	0.22458	0.000	σ_4	1	0.0006	0.00060	0.753
μ_2	1	0.1612	0.16115	0.000	σ_5	1	0.0009	0.00091	0.700
μ_3	1	0.3285	0.32853	0.000	σ_6	1	0.0013	0.00134	0.639
μ_4	1	0.0910	0.09102	0.000	σ_7	1	0.0023	0.00229	0.541
μ_5	1	0.0834	0.08337	0.000	σ_8	1	0.0005	0.00053	0.768
μ_6	1	0.0834	0.08218	0.001	*Error*	38	0.2285	0.00601	
μ_7	1	0.0294	0.02944	0.033	*Total*	54	65.1192		
μ_8	1	0.0429	0.04289	0.011					
σ_1	1	0.0001	0.00013	0.882					
σ_2	1	0.0049	0.00486	0.374					

(s = 0.0775407, R-sq. (adj)= 99.50%, R-sq. (pred)= 99.23%)

(b) RELIABILITY (Y2).

Source	*df*	*Adj SS*	*Adj MS*	*P-Value*	*Source*	*df*	*Adj SS*	*Adj MS*	*P-Value*
Regression	14	34.3704	2.45503	0.000	σ_2	1	0.0157	0.01568	0.568
μ_1	1	0.0716	0.07163	0.226	σ_4	1	0.0473	0.04732	0.324
μ_2	1	0.3068	0.30681	0.015	σ_5	1	0.0036	0.00356	0.785
μ_3	1	0.3532	0.35320	0.009	σ_6	1	0.0053	0.00531	0.740
μ_4	1	0.5494	0.54941	0.002	σ_7	1	0.0746	0.07457	0.217
μ_5	1	1.5120	1.51198	0.000	σ_8	1	0.0007	0.00067	0.906
μ_6	1	0.6526	0.65260	0.001	***Error***	40	1.8967	0.04742	
μ_7	1	0.57721	0.57721	0.001	***Total***	54	36.2671		
μ_8	1	0.0129	0.01287	0.605					

(s = 0.217758, R-sq. (adj) = 92.94% **,** R-sq. (pred) = 90.39%)

(c) DEPENDABILITY (Y3).

Source	*df*	*Adj SS*	*Adj MS*	*p-Value*	*Source*	*df*	*Adj SS*	*Adj MS*	*p-Value*
Regression	23	28.9405	1.25828	0.000	σ_5	1	0.0109	0.01094	0.532
μ_1	1	0.4144	0.41437	0.000	σ_6	1	0.1066	0.10662	0.057
μ_2	1	0.3801	0.38014	0.001	σ_7	1	0.0272	0.02718	0.326
μ_3	1	0.0381	0.03813	0.247	σ_8	1	0.0002	0.00022	0.929
μ_4	1	0.2518	0.25178	0.005	$\mu_1\mu_1$	1	0.4967	0.49666	0.000
μ_5	1	0.0939	0.09393	0.073	$\mu_1\mu_2$	1	0.3439	0.34393	0.001
μ_6	1	0.3317	0.33171	0.001	$\mu_1\mu_4$	1	0.2670	0.26702	0.004
μ_7	1	0.1046	0.10457	0.060	$\mu_2\mu_3$	1	0.0926	0.09262	0.075
μ_8	1	0.0001	0.00007	0.960	$\mu_3\mu_3$	1	0.0146	0.01461	0.470
σ_1	1	0.0420	0.04202	0.224	$\mu_6\mu_6$	1	0.2901	0.29011	0.003
σ_2	1	0.0087	0.00867	0.577	$\mu_7\mu_7$	1	0.0925	0.09247	0.075
σ_3	1	0.0057	0.00567	0.652	*Error*	31	0.8474	0.02734	
σ_4	1	0.0076	0.00756	0.603	*Total*	54	29.7879		

(s = 0.165336, R-sq. (adj) = 95.04%**,** R-sq. (pred) = 91.38%)

(d) FATIGUE SAFETY FACTOR (Y_4).

Source	*df*	*Adj SS*	*Adj MS*	*p-Value*	*Source*	*df*	*Adj SS*	*Adj MS*	*p-Value*
Regression	22	39.8252	1.81024	0.000	σ_5	1	0.0077	0.00766	0.610
μ_1	1	0.1376	0.13762	0.036	σ6	1	0.0004	0.00038	0.909
μ_2	1	0.0140	0.01404	0.491	σ7	1	0.0026	0.00255	0.768
μ_3	1	0.0304	0.03041	0.313	σ 8	1	0.0010	0.00096	0.856
μ_4	1	0.0780	0.07799	0.110	σ 4	1	0.0189	0.01885	0.425
μ_5	1	0.2808	0.28076	0.004	*μ1 μ2*	1	0.0293	0.02931	0.321
μ_6	1	0.0026	0.00261	0.766	*μ2 μ3*	1	0.0021	0.00210	0.789
μ_7	1	0.0001	0.00010	0.953	*μ1 μ3*	1	0.1166	0.11664	0.053
μ_8	1	0.0279	0.02787	0.333	*μ1 μ4*	1	0.0224	0.02239	0.385
σ_1	1	0.0050	0.00503	0.679	*μ2 μ4*	1	0.0987	0.09867	0.074
σ_2	1	0.0177	0.01767	0.440	*μ3 μ4*	1	0.0001	0.00007	0.962
σ_3	1	0.0020	0.00201	0.794	Error	32	0.9242	0.02888	
					Total	54	40.7494		

(s = 0.169949, R-sq. (adj)= 96.17%**,** R-sq. (pred)= 90.86%)

PROPOSED CONCURRENT OPTIMIZATION MODEL

The optimization model for concurrent product design and process planning for the main components of the bicycle frame is presented in the following subsections.

A. CONSTRAINTS ON QUALITY RESPONSES' PREFERENCES

Typically, the quality response is categorized into three main types; the larger-the-better (LTB), the smaller-the-better (STB), and the nominal-the-best (NTB) type responses. Then, each quality response is represented by a suitable membership function. In this research, the frame mass (y_1, STB type response) is preferred to be as small as possible. Thus, the appropriate membership (MF_1) is formulated as follows:

$$MF_1 = \begin{cases} 1 & y_1 \le 1.2 \\ 1-\dfrac{y_1-1.2}{0.05} & 1.2 \le y_1 \le 1.25 \\ 0 & y_1 \ge 1.25 \end{cases} \qquad (1)$$

The y_1 goal constraints are (maximal allowable positive deviation ($\Delta^{+}_{y_1}$) = 0.05):

$$y_1 - \delta^{+}_{y_1} = 1.2 \qquad (2a)$$

$$\mu_1 + \frac{\delta^{+}_{y_1}}{\Delta^{+}_{y_1}} = 1 \qquad (2b)$$

$$0 \le \delta^{+}_{y_1} \le \Delta^{+}_{y_1} \qquad (2c)$$

Further, the reliability (y_2), dependability (y_3) and fatigue safety factor (y_4) are the LTB type responses. The appropriate membership functions (MF_2, MF_3 andMF_4) used to represent these quality responses are expressed respectively as:

$$MF_j = \begin{cases} 0 & y_j \le 0.98 \\ 1-\dfrac{0.99-y_j}{0.01} & 0.98 \le y_j \le 0.99 \\ 1 & y_j \ge 0.99 \end{cases} \quad , j=2,3,4 \qquad (3)$$

The goal constraints for y_2 to y_4 are formulated as (maximal allowable negative deviation $\Delta^{-}_{y_j}$; j = 2,…, 4 =0.01):

$$y_j + \delta^{-}_{y_j} = 0.99 \quad , j=2,\dots,4 \qquad (4a)$$

$$MF_j + \frac{\delta^{-}_{y_j}}{\Delta^{-}_{y_j}} = 1 \quad , j=2,\dots,4 \qquad (4b)$$

$$0 \le \delta^{-}_{y_j} \le \Delta^{-}_{yj} \quad , j=2,\dots,4 \qquad (4c)$$

B. FRAME DESIGN CONSTRAINTS

In components design, the optimal design mean (μ_j) and standard deviation (σ_j) should be determined. Let $U_{\mu j}$ and $L_{\mu j}$ represent the upper and lower limits of μ_j, respectively. Similarly, let $U_{\sigma j}$ and $L_{\sigma j}$ represent the upper and lower limits of σ_j, respectively. Let $\Delta^{+}_{\mu j}$ ($\Delta^{+}_{\sigma j}$) and $\Delta^{-}_{\mu j}$ ($\Delta^{-}_{\sigma j}$) denote the maximal allowable positive and negative deviations of μ_j (σ_j), respectively. Then, the corresponding goal constraints on *jth* mean are expressed as 5a -5f.

$$\mu_j + \delta^-_{\mu_j} \geq L_{\mu_j} \quad (5a)$$

$$\mu_j + \delta^-_{\mu_j} \leq U_{\mu_j} \quad (5b)$$

$$MF_{\mu_j} + \delta^+_{\mu_j} / \Delta^+_{\mu j} + \delta^-_{\mu_j} / \Delta^-_{\mu j} = 1 \quad (5c)$$

$$0 \leq \delta^+_{\mu_j} \leq \Delta^+_{\mu j} \quad (5d)$$

$$0 \leq \delta^-_{\mu_j} \leq \Delta^-_{\mu j} \quad (5e)$$

$$MF_{\mu j} \geq M_{\mu j} \quad (5f)$$

where $M_{\sigma j}$ is the threshold value of $MF_{\sigma j}$. Next, the constraints on design means were formulated utilizing the level values of the design means and standard deviations shown in Table 3. For example, the constraints on the design mean and standard deviations, μ_1 and σ_1, respectively, are expressed sequentially as follows:

$$\mu_1 + \delta^-_{\mu_1} \geq 30 \quad (7a)$$

$$\mu_1 + \delta^-_{\mu_1} \leq 34 \quad (7b)$$

$$MF_{\mu_1} + (\delta^+_{\mu_1} + \delta^-_{\mu_1}) / 0.5 = 1 \quad (7c)$$

$$0 \leq \delta^{-,+}_{\mu_1} \leq 0.5 \quad (7d)$$

$$MF_{\mu 1} \geq 0.90 \quad (7e)$$

and

$$\sigma_1 + \delta^-_{\sigma_1} \geq 0.11 \quad (8a)$$

$$\sigma_1 - \delta^+_{\sigma_1} \leq 0.3 \quad (8b)$$

$$MF_{\sigma_1} + (\delta^+_{\sigma_1} + \delta^-_{\sigma_1}) / 0.01 = 1 \quad (8c)$$

$$0 \leq \delta^{+,-}_{\sigma_1} \leq 0.01 \quad (8d)$$

$$MF_{\sigma 1} \geq 0.90 \quad (8e)$$

The constraints on the remaining design mean and standard deviations are written in a similar manner.

C. Process planning constraints

In process planning, the preferences on process means (u_j) and standard deviations (s_j) were determined based on process knowledge and then displayed in Table 9.

where $M_{\mu j}$ is the threshold value of $MF_{\mu j}$. In a similar manner, the goal constraints on the *jth* standard deviation are formulated as 6a-6f.

$$\sigma_j + \delta^-_{\sigma_j} \geq L_{\sigma_j} \quad (6a)$$

$$\sigma_j + \delta^-_{\sigma_j} \leq U_{\sigma j} \quad (6b)$$

$$MF_{\sigma_j} + \delta^+_{\sigma_j} / \Delta^+_{\sigma_j} + \delta^-_{\sigma_j} / \Delta^-_{\sigma_j} = 1 \quad (6c)$$

$$0 \leq \delta^+_{\sigma_j} \leq \Delta^+_{\sigma_j} \quad (6d)$$

$$0 \leq \delta^-_{\sigma_j} \leq \Delta^-_{\sigma_j} \quad (6e)$$

$$MF_{\sigma_j} \geq MF_{\sigma} \quad (6f)$$

TABLE 9. PREFERENCES ON PROCESS MEANS AND STANDARD DEVIATIONS.

	Lower u_j	Upper u_j		Lower s_j	Upper s_j
u_1	30	34	s_1	0.06	0.2
u_2	27	34	s_2	0.09	0.25
u_3	31	35	s_3	0.10	0.31
u_4	26	30	s_4	0.10	0.25
u_5	17	21	s_5	0.07	0.17
u_6	12	16	s_6	0.05	0.12
u_7	18	22	s_7	0.07	0.18
u_8	13	17	s_8	0.05	0.15

Adopting the means' and standard deviations' upper and lower values in Table 9, the constraints on u_j and s_j were established. For example, the constraints on u_1 and its corresponding s_1 are formulated respectively as follows:

$$u_1 + \delta^-_{u_1} \geq 30 \quad (9a)$$

$$u_1 + \delta^-_{u_1} \leq 34 \quad (9b)$$

$$MF_{u_1} + (\delta^+_{u_1} + \delta^-_{u_1}) / 0.5 = 1 \quad (9c)$$

$$0 \leq \delta^{-,+}_{u_1} \leq 0.5 \quad (9d)$$

$$MF_{u1} \geq 0.90 \quad (9e)$$

and

$$s_1 + \delta^-_{s_1} \geq 0.06 \quad (10a)$$

$$s_1 - \delta^+_{s_1} \leq 0.2 \quad (10b)$$

$$MF_{s_1} + (\delta^-_{s_1} + \delta^+_{s_1}) / 0.01 = 1 \quad (10c)$$

$$0 \leq \delta^{-,+}_{s_1} \leq 0.01 \quad (10d)$$

$$MF_{s_1} \geq 0.90 \quad (10e)$$

In a similar manner, the constraints on the remaining u_j and s_j are developed.

D. Product-process constraints

The process capability index, c_{pm}, relates the product specifications with process mean and standard deviation. Larger c_{pm} indicates higher ability of the process to produce conforming products within the specification limits. In this research, it is assumed that each product element is produced by distinct process. The acceptable range of c_{pm} index is between 1.5 and 2.5 for each manufacturing process. Then, the capability constraints for each process are formulated as:

$$c_{pmj} = \sigma_j / \left[(u_j - \mu_j)^2 + s_j^2 \right]^{0.5} \qquad j=1,\ldots,8 \qquad (11a)$$

$$1.5 \le c_{pmj} \le 2.5 \qquad j=1,\ldots,8 \qquad (11b)$$

Another constraint is formulated to guarantee functionality, which is written as follows:

$$\left| \mu_j - u_j \right| \le 3\sigma_j - 3s_j \quad , \; j=1,\ldots,8 \qquad (12)$$

V. Formulating objective functions

The objective functions are formulated to:

- Minimize the weighted sum of the positive and negative deviations for the four quality responses; $d_{y1}^{+}/0.05 + d_{y2}^{-}/0.01 + d_{y3}^{-}/0.01 + d_{y4}^{-}/0.01$.
- Minimize the weighted sum of the positive and negative deviations for the design means and standard deviations; $(\sum_{j=1}^{8}(d_{\mu j}^{+} + d_{\mu j}^{-}) + (\sum_{j=1}^{8}(d_{\sigma j}^{+} + d_{\sigma j}^{-})$
- Minimize the weighted sum of the positive and negative deviations of process means and standard deviations; $\sum_{j=1}^{8}(d_{uj}^{+} + d_{uj}^{-}))/0.5 + \sum_{j=1}^{8}(d_{sj}^{+} + d_{sj}^{-}))/0.01$
- Maximize the multiplication of the processes capability indices; $(\prod_{j=1}^{8} c_{pm\,j})^{0.125}$

The four objective function can be combined into a single objective function as follows:

$$\begin{aligned} Min\ z &= d_{y1}^{+}/0.05 + d_{y2}^{-}/0.01 + d_{y3}^{-}/0.01 + d_{y4}^{-}/0.01 + \\ & (\sum_{j=1}^{8}(d_{\mu j}^{+} + d_{\mu j}^{-}) + \sum_{j=1}^{8}(d_{uj}^{+} + d_{uj}^{-}))/0.5 + (\sum_{j=1}^{8}(d_{\sigma j}^{+} + d_{\sigma j}^{-}) \\ & + \sum_{j=1}^{8}(d_{sj}^{+} + d_{sj}^{-}))/0.01 - (\prod_{j=1}^{8} c_{pm\,j})^{0.125} \end{aligned} \qquad (13)$$

Optimization Results

The complete optimization model is formulated by combining formulas 2 to 14 and then solved using Ling 11 software package. It should be mentioned that the minimal acceptable satisfaction levels for each of responses, controllable factors, and process means and standard deviations are all set values of 90% in the complete optimization model. Table 10 displays the obtained optimization results for the design means, μ_j^*, and standard deviations, σ_j^*, as well as the corresponding optimal values for process means, u_j^*, and standard deviations, s_j^*. These optimal values provide at least 90 % satisfaction level. At the optimal means and standard deviations, the obtained values of the four responses y_1, y_2, y_3, and y_4; y_1*, y_2*, y_3*, and y_4*, respectively, are calculated as 1.0824, 1.00, 0.99, and 0.99, respectively. These quality responses are achieved with at least 90 % level of satisfaction. Moreover, all the obtained values of c_{pm}^* are equal to 1.5, which indicates acceptable capability levels of manufacturing processes.

Conclusions

This research adopted an effective proposed methodology for optimal product design and process planning of bicycle frame via simulation and fuzzy goal programming. Four quality responses were of main concern, including mass, reliability, dependability, and fatigue safety factor. Initially, the frame design was developed. Eight key design parameters with their associated tolerances of the critical bicycle frame were then identified. Moreover, eight process controllable means with their corresponding tolerances were determined. Follows, the experimental design was conducted utilizing the Taguchi's array. Simulation was performed at each combination of the design means and standard deviations of the key components of the bicycle frame. Fit of probability distributions for mass, stress, deformation, fatigue safety factor followed. Finally, the optimization model was developed and then solved to obtain the optimal design means and tolerances for product design with their corresponding processes means and standard deviations. The results showed that the developed optimization model is found efficient in achieving high satisfaction levels on the desired quality responses and process capability index. In conclusion, this methodology can provide values assistance to product and process engineers in finding the optimal concurrent product design and process planning in a wide range of design applications.

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TABLE 10. OPTIMIZATION RESULTS.

Variable	*Optimal value*	*Variable*	*Optimal value*	*Variable*	*Optimal value*	*Variable*	*Value*	*Variable*	*Value*
$\mu1^*$	30.11351	$u1^*$	30.01708	$\sigma1^*$	0.2183007	$s1^*$	0.1090000	$cpm1$	1.500
$\mu2^*$	26.97308	$u2^*$	27.00000	$\sigma2^*$	0.2500000	$s2^*$	0.1644777	$cpm2$	1.500
$\mu3^*$	31.18141	$u3^*$	31.00000	$\sigma3^*$	0.3100000	$s3^*$	0.0990000	$cpm3$	1.500
$\mu4^*$	25.97308	$u4^*$	25.97308	$\sigma4^*$	0.2500000	$s4^*$	0.1666667	$cpm4$	1.500
$\mu5^*$	17.24293	$u5^*$	17.25865	$\sigma5^*$	0.1061522	$s5^*$	0.0690000	$cpm5$	1.500
$\mu6^*$	15.93676	$u6^*$	16.00000	$\sigma6^*$	0.1200000	$s6^*$	0.0490000	$cpm6$	1.500
$\mu7^*$	17.97308	$u7^*$	17.95000	$\sigma7^*$	0.1105586	$s7^*$	0.0700000	$cpm7$	1.500
$\mu8^*$	13.03660	$u8^*$	12.95000	$\sigma8^*$	0.1500000	$s8^*$	0.0500000	$cpm8$	1.500
y_1^*	1.082432	y_2^*	1.000000	y_3^*	0.990000	y_4^*	0.990000		

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AUTHOR INFORMATION

Prof. Al-Rafaie is currently working in the department of Industrial Engineering at the University of Jordan. He has published more than 100 articles in reputable international journals and participated in more than 15 international conferences. He was awarded the "Ali Mango Award for distinguished researcher in Science in Jordan, 2018". He was also awarded the award for distinguished researcher in Science in the University of Jordan for years 2012 and 2013. His research focuses on Engineering management, Robust design, Optimization, Scheduling and sequencing modeling, Quality engineering.