Table 4 Results of the SNR variable for model 2 in the simulation process from 1 to 500 iterations

Experiment	SNR max	Iteration	Percentage Value	Weighted Value
1-10	27.1620	1	-0.3004	-0.3004

Table 8 shows the results of the maximum values of the ($\widehat{SNR}$) variable for model 3, and these values do not present a significant difference. However, the weighted value shows that the best experiments are 4, 5, 9, and 10 with percentage values of 1.7156, 1.7180, 1.7157, 1.7181, and weighted values of 0.0093, 0.116, 0.0094, and 0.0118 respectively.

Table 5 Results of the SNR variable for model 3 in the simulation process from 1 to 500 iterations

Experiment	SNR max	Iteration	Percentage Value	Weighted Value
1	60.8754	500	1.7049	0.0034
2	60.8752	500	1.7049	0.0034
3	60.9415	500	1.7079	0.0034
4	61.1154	185	1.7156	0.0093
5	61.1700	148	1.7180	0.0116
6	60.8755	500	1.7049	0.0034
7	60.8754	500	1.7049	0.0034
8	60.9429	500	1.7079	0.0034
9	61.1169	183	1.7157	0.0094
10	61.1712	146	1.7181	0.0118

Table 9 shows the results of the maximum values of the response variable $\widehat{SNR}$ of model 4; these values are between 30.7588 and 30.9313. The difference between these values is not significant, although in terms of the number of iterations, the difference is very significant since their minimum values of iterations are between 48 and 58. The weighted value shows that the best experiments are 6 and 7, with values of 0.1514 and percentage value of 7.2664 for both experiments.

Table 6 Results of the SNR variable for model 4 in the simulation process from 1 to 500 iterations

Experiment	SNR max	Iteration	Percentage Value	Weighted Value
1	30.7592	49	7.2665	0.1483
2	30.7592	49	7.2665	0.1483
3	30.8670	54	7.2955	0.1351
4	30.9313	58	7.3127	0.1261
5	30.7836	50	7.2730	0.1455
6	30.7588	48	7.2664	0.1514
7	30.7588	48	7.2664	0.1514
8	30.8571	53	7.2928	0.1376
9	30.9171	56	7.3089	0.1305
10	30.7813	49	7.2724	0.1484

4.2 Graphical Results

Figure 1 below shows the weighted values from the ten experiments analyzed to optimize the response variable $\widehat{SNR}$ evaluated in the four models proposed in this work. Where it can be seen that experiments 3 and 5 are those reaching the higher values for the four models.

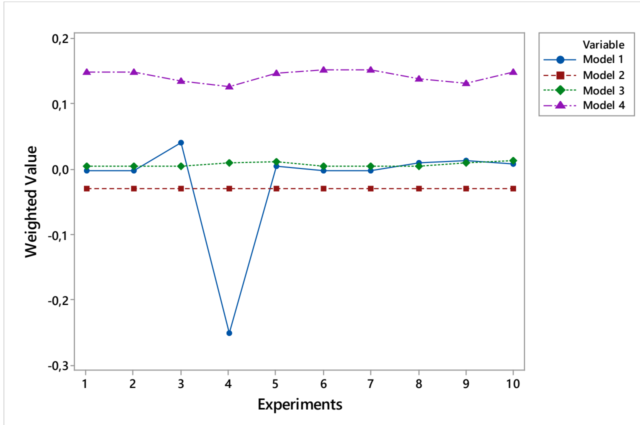

Figure 1 Weighted values for each experiment evaluated in models 1, 2, 3, and 4 at 500 iterations.

The results obtained in this research show that the difference between the results of each experiment is relatively small. Only in model 1 a significant change is observed between the results of ten experiments, which does not happen in the results obtained in the evaluations of models 2, 3 and 4 in which the maximum values obtained are practically the same in all 10 experiments.

5. Conclusion

This research proposes an SPSA algorithm to maximize the signal-to-noise ratio ($\widehat{SNR}$) in the least number of iterations, and it is also sought to determine which of the succession measures cited in the literature of this algorithm converge to maximize these quality indices that evaluate. The results show that the proposed SPSA algorithm maximizes the ($\widehat{SNR}$) for the four case studies in this research.

Another objective of this work is to improve by at least 10% the results reported by the authors of each case study analyzed. It is important to highlight that this objective was not achieved. However, there were improvements, greater than 2% for model 1, greater than 1% in model 3, and greater than 7% in model 4, only in model 2 there was no percentage improvement.

Furthermore, the succession measures that converge on the maximum values of the variable ($\widehat{SNR}$) that its combinations of experiments of the succession measures for the proposed SPSA algorithm in the four case studies are 3 and 5.

Finally, the results obtained show that the proposed SPSA algorithm is an easily implemented, efficient, and iterative method, which can be considered as an experimental tool for the improvement of quality indices that evaluate the aptitude of the processes within the Six Sigma methodology.

Future research should propose a Stochastic Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm capable of working with discrete and mixed controllable factors, and that is robust to the process quality indices to be optimized with the succession measures evaluated in this research.

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