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An efficient design of primary sedimentation tanks using a combination of response surface, metaheuristic and scenario building

M. Zamani, A. Montazeri, M. Gheibi, A. Fathollahi, K. Behzadian

Abstract

Solid particle sedimentation is assumed as a complex procedure in both water and wastewater treatment plants. There is a great deal of interest in applying and developing different simulation and optimization methods to design a primary sedimentation tanks (PSTs). In traditional techniques, mechanical and physical parameters are set by sequential error loops. To eliminate the disadvantage of existing techniques, this study proposes a hybrid method based on the response surface methodology, efficient metaheuristics and scenario building methods using different experimental methods. This novel framework creates a robust and sustainable design for the PSTs. First of all, the parameters of the considered PST based on the economic, improve process and tank efficiency scenarios are tuned and optimized by the Central Composition Design (CCD) and Response Surface Methodology (RSM). To forecast an efficient response value for these scenarios, different metaheuristic algorithms including the Genetic Algorithm (GA), Pattern Search Algorithm (PSA) and Simulate Annealing Algorithm (SAA) are applied. Results demonstrated that PSA, GA and PSA with 0.02, 0.032 and 0.063 in comparison with experimental practices have the best calibration for prediction of response in economic, improve process and tank efficiency scenarios, correspondingly. Finally, experimental tests have proven that the optimum Retention Time (RT) is equal to 2 hours based on the biological oxygen demand and the total suspended solids eliminations in the lab-scale setup.

Keywords: Primary Sedimentation Tanks, Response Surface Methodology, Metaheuristic Algorithms, Scenario Building Methods.

1. Introduction

Recent technologies on wastewater treatment and new designing methods of effluent recycling have a magnificent influence on people's future lives. This significant influence comes from the importance of the recovered water as a new-possible supply of resource. Water and wastewater treatment have been named "the greatest challenge of the 21st century". Consequently, this claim supports and proves the points mentioned earlier (Mujeriego and Asano, 1999; Jover-Smet et al., 2017; ShahrokhiMahdi et al., 2012). Wastewater treatment contains some methods like physical, chemical, and biological treatments. Physical decontamination is one of the most crucial parts of the wastewater treatment process because it will reduce much pollution of the water such as Suspended Solids (SS) and hydro soluble chemicals. Moreover, it increases the efficiency of the treatment by working well during the process (Jover-Smet et al., 2017; ShahrokhiMahdi et al., 2012; Sher et al., 2020; Polorigni et al., 2021; Athanasia et al., 2008). Primary Sedimentation is the first, influential, and actual physical treatment process because of gravity, which extensively applies in water and wastewater physical treatment (ShahrokhiMahdi et al., 2012). These pollutants (SS & hydro soluble chemicals) are the main components of the wastewater and can be found in large portions. The tremendous direct or indirect influence of these contaminations on the living of organisms by bio magnification is undeniable (Sher et al., 2020).

Primary sedimentation is included by some complicated physical processes that separate solid and liquid pollutants, making a separable solution in Primary Sedimentation Tanks (PSTs). Hence, introducing models which can precisely describe this manner has been one of the most significant and most challenging problems during recent researches (Polorigni et al., 2021). PSTs contain turbulence flow fields that influence the efficiency of the process. therefore, some particles that have been settled during the process may go into a re-suspension procedure, which wastes the past attempts, if the turbulence does not prognosticate before the turbulence's beginning (ShahrokhiMahdi et al., 2012). Many factors like tank's class, solid elimination mechanism, loading degree, etc., will influence the efficiency and capability of a PST. Consequently, recent designers, for example, are trying to oversize the PSTs as a respondent to poor design, which is the leading cause of system disorders and turbulences (Athanasia et al., 2008).

As an acknowledgment to demonstrate the significance of this research in the literature, there have been many associated and essential records reviewed as follows. Sedimentation of SS in a solution owing to the gravitational primary sedimentation process has been an essential topic for decades. Since Stokes, 1851 expressed an equalization to demonstrate the activity rate of sedimentation of SS under the sheet-laminar flow position (Bustos et al., 1999; Jover-Smet et al., 2017). A scientific approach was manifested in the 1970s, striving to ally presentations on sedimentation of dispersed and flocculating suspensions (ShahrokhiMahdi et al., 2012; Concha et al., 2002). Hazen,1904 observed the opening exposition of circumstances that affected the sedimentation of dense, hard scraps and introduced the outside charging theory (Concha et al., 2002). An active approach of sedimentation arises from concentration changes valid for theoretical suspensions was encountered by Kynch in 1952 (Athanasia et al., 2008; Concha et al., 2002). Christoulas et al., in 1998, developed an experimental design for the primary sedimentation process. This model gives a good result in the model's efficiency while testing under the combined analysis of three well-correlated sets of data (Christoulas et al., 1998). Shahrokhi et al., in 2013, initiated an investigation on the suiTable baffle, which helps the PST to have a calm-streamline flow field. They found an accurate position and height of a baffle in a rectangular primary sedimentation tank (Shahrokhi et al., 2013). Vahidifar et al., in 2018, submitted the theory of successful settling to evaluate and optimize the PSTs with the cooperation of different methods. They examined these elemental methods applying the short-circuiting phenomenon and the successful settling theory (Vahidifar et al., 2018).

Simple elementary evaluation on the preceding-declared researches will show that none of them use one required combination. The mixture of experimental, statistical analysis and evolutionary methods for evaluating the optimization of the PSTs. Consequently, the development of an efficient PST can be considered as a research gap. Optimization models play a crucial role in designing PSTs because of their serious sensitiveness. They will boost the design, and by this cooperation, the process will encounter fewer errors.

The main targets of this paper are to satiate this research gap by the plan which are set out as follows:

(i) Defining cost functions for designing PSTs based on economic, process modification, and reactor efficiency.
(ii) Optimizing the functional parameters for PST design by applying the Central Composition Design (CCD) and Response Surface Methodology (RSM).
(iii) Sensitive analysis of designing as per Scenario Building Method (SBM).
(iv) Applying Genetic Algorithm (GA), Pattern Search Algorithm (PSA) and Simulate Annealing Algorithm (SAA) for calibrating non-linear regression predictive equations.
(v) Validating the models with real experimental hydraulic testing in lab-scale setup.

Other sections of this paper are summarized as follows: Section 2 explores the materials and methods including the framework of this research, used statistical and numerical methods, lab-scale setup and SBM assumptions. Section 3 provides an extensive analysis and in-depth discussion from results. Finally, Section 4 reviews a summary for this paper with recommendations and future research opportunities.

2. Materials and methods

2.1. Case study and experiments

The present research is done for optimizing the PST of industrial wastewater treatment plant which is located in Mashhad city, Iran as per Fig. 1. Likewise, the average specification of the mentioned case study is summarized based on Table 1.

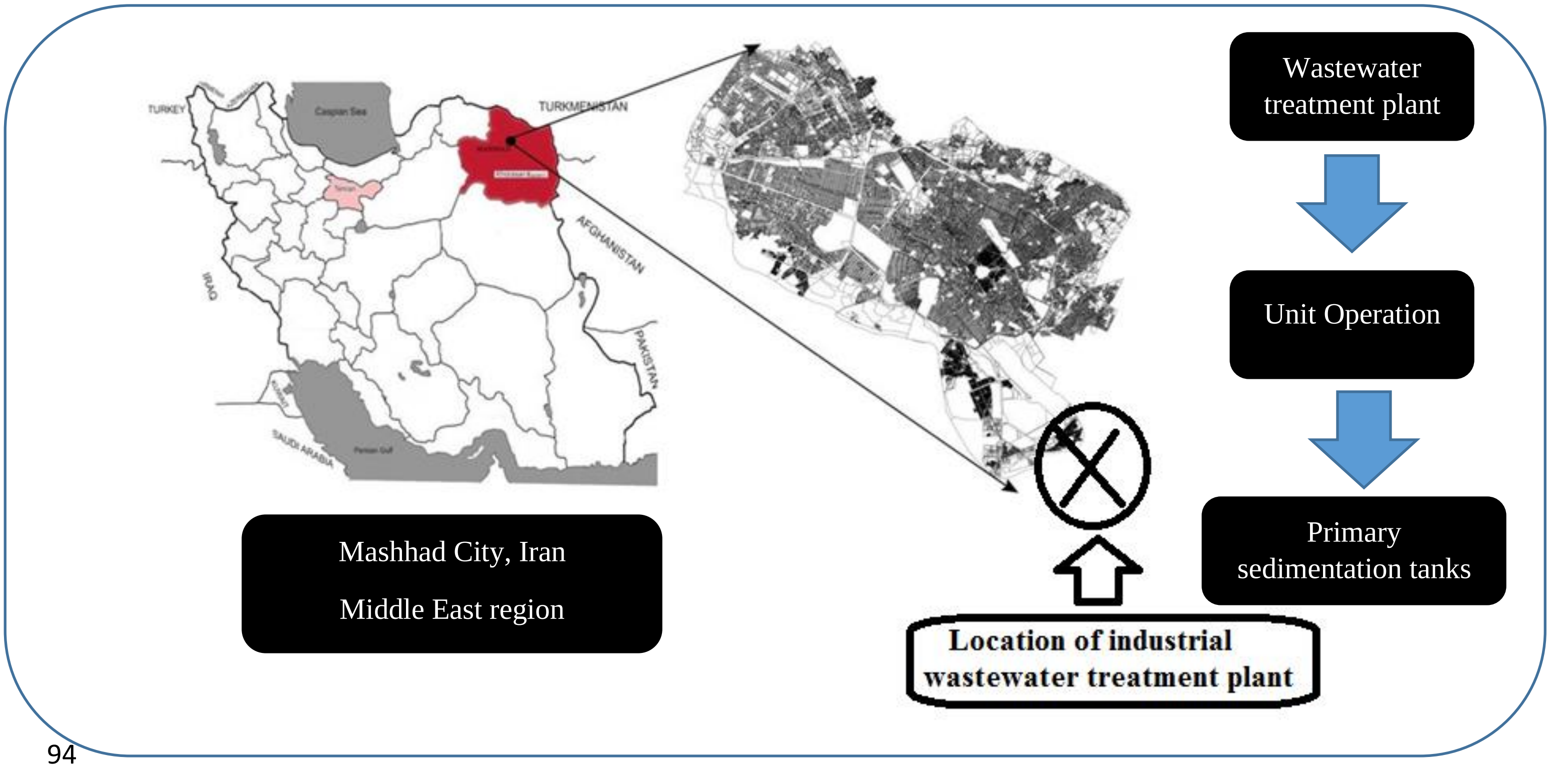


Fig. 1. Location of industrial wastewater treatment plant in Mashhad, Iran.

In the end of statistical modelling and optimizations, for comparing the results of each mathematical model such as GA, PSA and SAA, some experimental runs are done in lab-scale adjustable setup according to Fig. 2. The mentioned environmental hydraulic lab is located in Mashhad city. In each run, the optimum conditions of PST design are set in size adjustable lab-scale setup and the outcomes of it is asset. Plus, the experimental results are compared with output of each mathematical model and they are authorized in this method as per error value. The mentioned setup is invented by Poly (methyl methacrylate) (PMMA) material and also, for experimental evaluations, all optimum dimensions are scaled in lab scale setup.

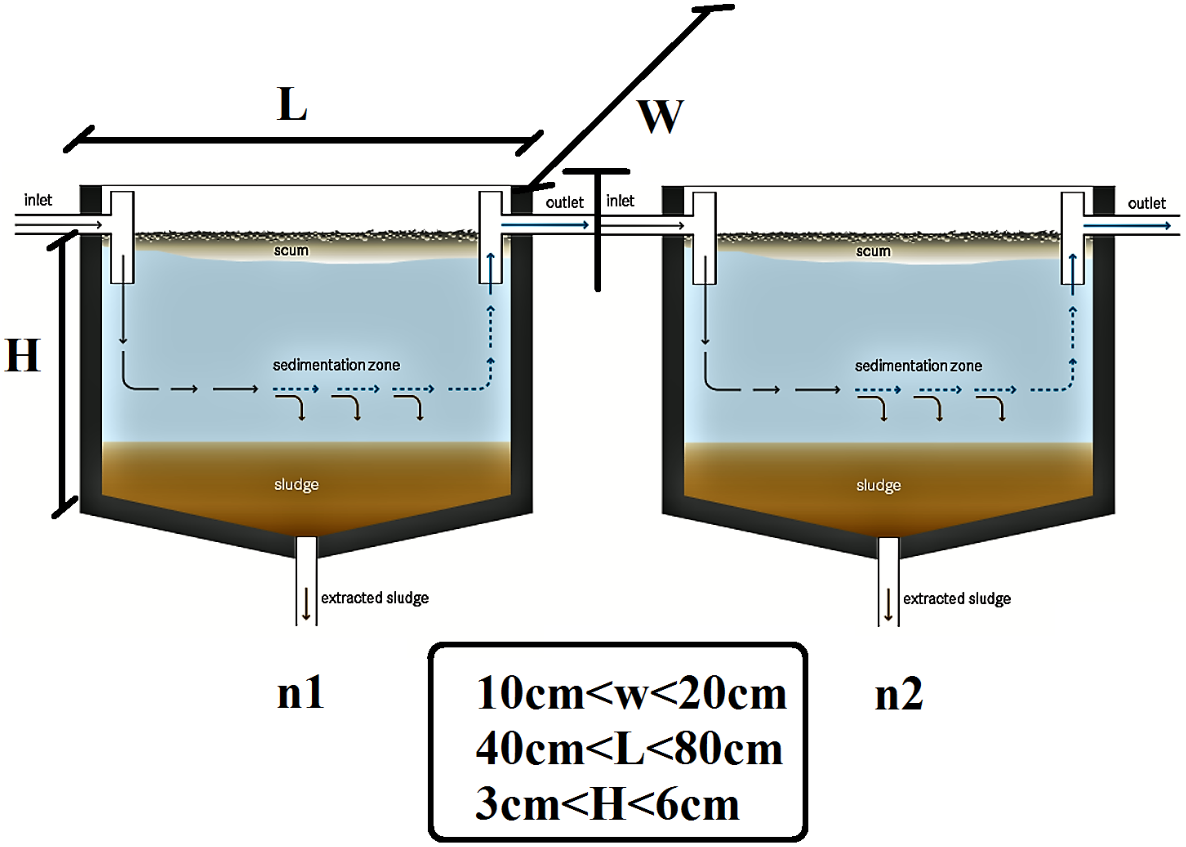


Fig. 2. Schematic plan of lab scale PST in present study.

Table 1. Specification of raw wastewater in present research.

Parameter	**Unit**	**Value**
Wastewater flow	m^3/h	210
Chemical Oxygen Demand	mg/l	780
Total Suspended Solid	mg/l	325
Temperature	$_{o}$C	21
pH	——	8.2
Dissolved Oxygen	mg/l	6.4

2.2.Research methodology

The research methodology of present study is illustrated in Fig. 3 which is divided to four sections containing statistical computations, SBM implementation, numerical calculations and experimental practices. First, the algorithm of CCD-RSM is run and then different designing/reengineering situations are appraised by SBM. The outcomes of SBM are optimized by three GA, PSA and SAA algorithm. For judging between the declared optimization methods, some experimental evaluations are done in lab scale setup.

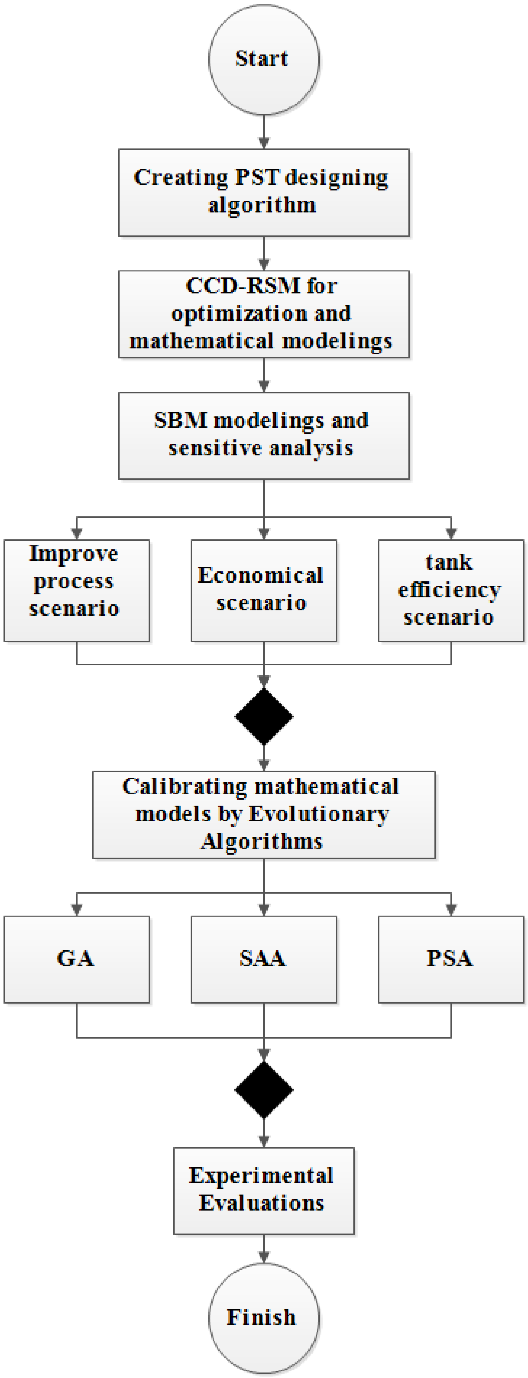


Fig. 3. Research methodology in the present study.

2.3.Proposed PST

To design PSTs, usage of Fluid Mechanic’s Continuity relations is undeniable. By assuming the mean wastewater flow as 'Q Ave' and the maximum flow as 'Q Max', PSTs’ designing algorithm is illustrated in Fig. 4 (Kirishima et al., 2021; Xu et al., 2021).

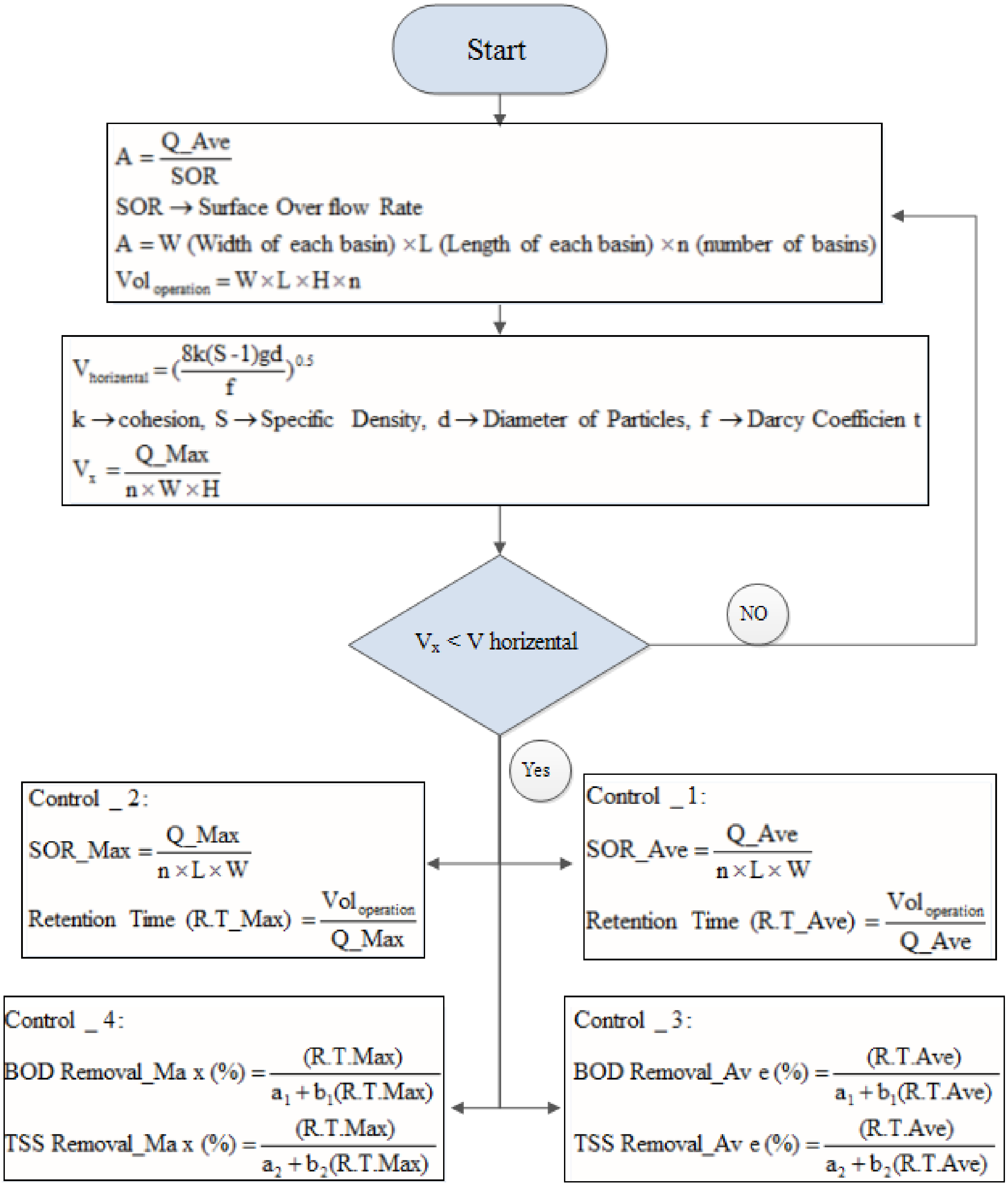


Fig. 4. PSTs' computational design

a1 = 0.018, b1 = 0.020, a2 = 0.0075, b2 = 0.014 (Vesilind, 2013; Henze et al., 2008; Russell, 2019)

As shown in Fig. 2, the number of tanks (n), the Width of any rectangular tank (W), Length of the tanks (L), the Height of the tank (H), and the Surface Overflow Rate (SOR) should be determined as the first step of designing. In the following, the design will be developed, and according to Fig. 4, the computation of all the system's members will be done. Hence, using the CCD-RSM algorithm (Vesilind, 2013; Henze et al., 2008; Russell, 2019) is indisputable for the optimization of the design's features and effective parameters. The introduced algorithm model is utilized in the MATLAB 2018b® program to run each test inside it.

2.4.Proposed CCD-RSM

All the model's input and objective functions should be determined in the RSM optimization model. According to the previously mentioned information (Fig. 4), the model's input factors are containing the Number of tanks (n), the Width of any rectangular tank (W), Length of the tanks (L), the Height of the tank (H), and the Surface Overflow Rate (SOR). The quantity of these factors is shown as per Table 2 which are considered based on the literature review and main resources of wastewater treatment plant designing (Karia and Christian, 2013; Benefield et al., 1984; Edward, 2019). All CCD-RSM computations are done in Design Expert 7.0.0 software (Eftekhari et al., 2020; Eftekhari et al., 2021).

Table 2. Input parameters in CCD-RSM model to design the PSTs.

Parameter	Unit	Minimum (-1)	Mean (0)	Maximum (+1)
Number of tanks (n)	-	2	3	4
Width of any rectangular tank (W)	m	3	13.5	24
Length of the tanks (L)	m	15	52.5	90
Height of the tank (H)	m	3	4	5
Surface Overflow Rate (SOR)	$m^3.m^{-2}.d^{-1}$	30	40	50

Objective functions should be determined to evaluate the process of each sketched test. In this part of the design, objective functions have economic, process and efficiency issues. Economic functions depend on construction's cost, volume, and the number of the PSTs (F1) while the process functions rely on the four constraints shown in Fig. 2. Also, the efficiency functions are related to Biochemical Oxygen Demand (BOD) and Total Suspended Solid (TSS) elimination. All these functions are shown in Table 3. The mentioned functions are designed according to basic equations (Metcalf et al., 1991; Tchobanoglous et al., 2003) and just, through this study, the functions are converted to error formula in comparison of ideal values as per basic references.

Table 3. Objective functions in the CCD-RSM model to design PSTs.

Number	Function's type	Optimization terms	Objective function's Equation
1	economic	minimum	$f_1 = n' \ W' \ L' \ H' \ \text{Constand Cost}$

2	Improving process	minimum	$f_2 = (SOR\_Max - 120)^2 + (SOR\_Max - 80)^2$
3	Improving process	minimum	$f_3 = (SOR\_Ave - 50)^2 + (SOR\_Ave - 30)^2$
4	Improving process	minimum	$f_4 = (R.T\_Max - 2.5)^2 + (R.T\_Max - 1.5)^2$
5	Improving process	minimum	$f_5 = (R.T\_Ave - 2.5)^2 + (R.T\_Ave - 1.5)^2$
6	Tank efficiency	maximum	$f_6 = \frac{(R.T.Max)}{a_1 + b_1(R.T.Max)}$
7	Tank efficiency	maximum	$f_7 = \frac{(R.T.Max)}{a_2 + b_2(R.T.Max)}$
8	Tank efficiency	maximum	$f_8 = \frac{(R.T.Ave)}{a_1 + b_1(R.T.Ave)}$
9	Tank efficiency	maximum	$f_9 = \frac{(R.T.Ave)}{a_2 + b_2(R.T.Ave)}$

According to the experimental information exist in the reference resources, the maximum quantity of SOR in PSTs should be 80-120 $m^3.m^{-2}$. s. Accordingly, the 'f2.' function is shaped based on the interval among the stated parameters and the maximum SOR quantity. This amount is balanced by 30-50 for the average SOR and is viewed in the 'f3.' function. 'f4.' and 'f5.' functions have deemed a controller to the Retention Time (RT) in 'Q Ave' and 'Q Max' terms with the minimum quantity of 1.5 hours and the maximum amount of 2.5 hours (Karia and Christian, 2013; Benefield et al., 1984; Edward, 2019). Moreover, the 'f6 - f9' functions are linked to the exclusion percentage of BOD and TSS values and are the same as the maximum functions.

2.5.SBM system

With due attention to the fact that 'f1-f9' functions are some maximum and some minimum functions, all these objective functions should convert to a dimensionless quantity during each test with incommensurable methods. In the following, the Relation Deviation Index (RDI) method will be used to make the numerical quantities of the objective functions dimensionless, as shown in Equation 1 (Erfani et al., 2019).

$$RDI = \frac{|f_i - f_{best}|}{|f_{max} - f_{min}|} \qquad \textbf{Equation 1}$$

After the incommensurability, different scenarios can be formed for the 'f1-f9' functions' interactions by weighting each function. Some of these scenarios are shown in Equation 2. Moreover, it is probable to use decision analysis' like Multi-Criteria Decision Making (MCDM) to weighting these functions. For determining each scenario’s weights, the Shannon Entropy (SE) method is performed, illustrated in Fig. 5 (Gheibi et al., 2019). Plus, eight experts, including five wastewater treatment plant designer and three system operators are interviewed in the present study. This problem can be analyzed and examined as a multi-purpose function too. But, because of the increasing number of objective functions, the convergent probability is much less. Consequently, by the scenarios shown in Equation 2, the predicament situation will converge to an exclusive destination response. In the declared Equation, as an indicator's weight is low; Its priority is powerful because the RDI approach will make all the functions least and minimum.

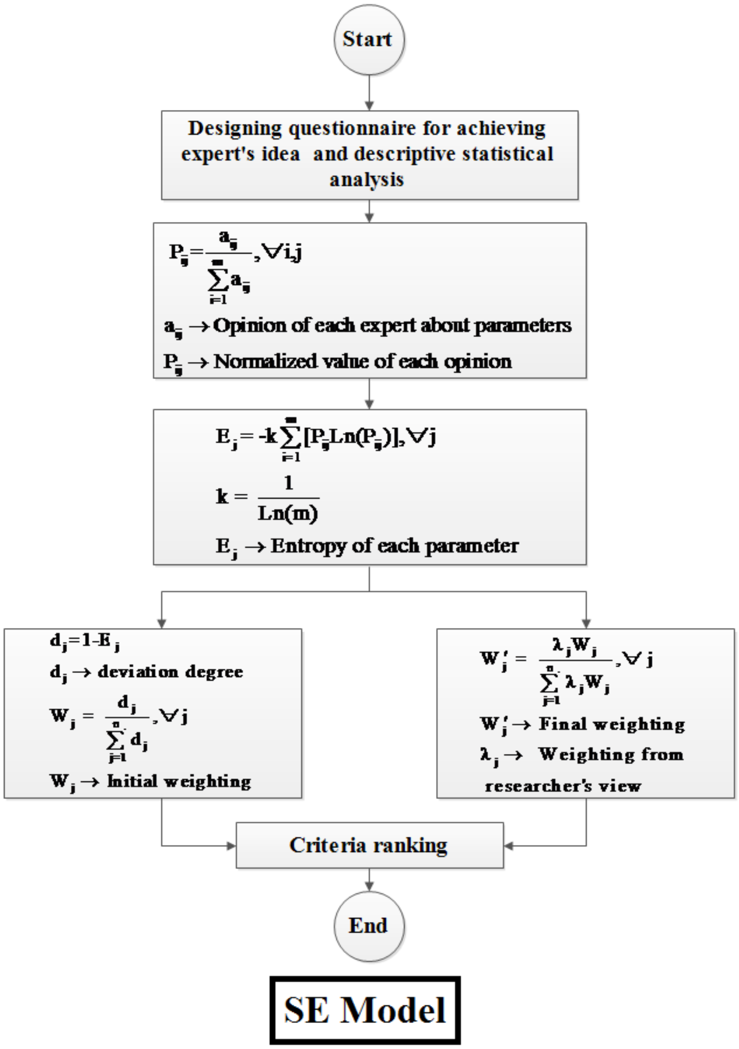


Fig. 5. Algorithm of SE computation in present investigation.

Equation 2

$$
\begin{aligned}
& f_{Total} = \sum w_i f_i \\
& \text{Scenario1 (Economical Scenario)} \rightarrow w_1 = 0.022, w_2 = 0.122, w_3 = 0.122 \\
& w_4 = 0.122, w_5 = 0.122, w_6 = 0.122, w_7 = 0.122, w_8 = 0.122, w_9 = 0.122 \\
& \text{Scenario2 (Improve Process Scenario)} \rightarrow w_1 = 0.164, w_2 = 0.04, w_3 = 0.04 \\
& w_4 = 0.04, w_5 = 0.04, w_6 = 0.164, w_7 = 0.164, w_8 = 0.164, w_9 = 0.164 \\
& \text{Scenario3 (Tank efficiency Scenario)} \rightarrow w_1 = 0.164, w_2 = 0.164, w_3 = 0.164 \\
& w_4 = 0.164, w_5 = 0.164, w_6 = 0.04, w_7 = 0.04, w_8 = 0.04, w_9 = 0.04
\end{aligned}
$$

Evaluating these Equations will reveal that scenarios 1, 2, and 3, are focusing on economic, process improvement, and tank efficiency, respectively. These scenarios can be regulated to satisfy the designer's and employer's demands. As per previous notices, all weights of Equation 2 are determined as per the opinion of 8 experts and they are computed based on the mean weight of gathered scores by experts. In each scenario, the study asked the experts to imagine the importance of economic, improve process, and tank efficiency are more than others through each scenario and then they assign scores. Finally, the functions are minimization type and because of this fact, the declared weights are reversed and then assigned.

Firstly, the PSTs design steps are outlined in the MATLAB programming facade. Secondly, tests are designed by the input parameters shown in Table 1 and CCD-RSM methods that are shown in Table 2. Moreover, the objective functions of each test, conducted in Table 3, are determined. After the non-scaling, the scenarios shown as per Equation 2, they will convert to an individual purpose function. Finally, all the test's and scenario's conditions will be evaluated in the designed model. It is necessary to mention that the sketch in CCD-RSM method is composed of 5 levels and the alpha factor is set equal to 1.2. Through the CCD-RSM computations, due to evaluation of response's fluctuations in the neighbor of maximum and minimum values of input data and rechecking the response of numerical boundaries based on output function values alpha factor is adjusted. About alpha factor, a value less than one puts the axial points in the cube; a value equal to one puts them on the faces of the cube; and a value greater than one puts them outside the cube. Therefore, with 1.2 amount, the variations of response are detected as safety factors of the optimization procedure. The exact value of alpha is determined based on the try and error method and the input parameters should be meaningful and in a logical range. In the Design Factor program, the minimum test numbers elected as 26 tests for five effective parameters. In Table 4 the "4.2" and "1.8" values are considered equal to "5" and "1" amounts, respectively, to be meaningful as n value.

Table 4. Producing the PSTs designs according to the RSM-CCD methods.

run	n	W	L	H	SOR
1	3	13.5	52.5	4	40
2	4	24	15	5	30
3	3	13.5	52.5	2.8	40
4	1.8	13.5	52.5	4	40

5	3	13.5	52.5	4	40
6	2	3	15	3	30
7	3	13.5	7.5	4	40
8	2	3	90	5	50
9	3	0.9	52.5	4	40
10	4	3	90	3	50
11	3	13.5	52.5	4	52
12	2	24	15	5	50
13	4.2	13.5	52.5	4	40
14	4	3	90	5	30
15	4	3	15	5	50
16	3	13.5	52.5	4	40
17	2	24	90	5	30
18	3	13.5	52.5	4	28
19	2	24	90	3	50
20	3	26.1	52.5	4	40
21	4	24	15	3	50
22	3	13.5	52.5	4	40
23	3	13.5	52.5	4	40
24	3	13.5	97.5	4	40
25	4	24	90	3	30
26	3	13.5	52.5	5.2	40

2.6.Proposed metaheuristics

In present research, after computing mathematical Equation from CCD-RSM, the outcomes of the mentioned computations will be calibrated by three GA, PSA and SAA algorithms as the efficient metaheuristic methods in the literature. We have used the Optim Tool of MATLAB platform. In the three GA, SAA and PSA algorithms adjustment parameters are set as per Equation 3-5, correspondingly. Since these metaheuristics have been defined in many relevant works, their description is not provided and referred to the recent papers: (Fathollahi-Fard et al., 2020a; Fathollahi-Fard et al., 2020b; Fathollahi-Fard et al., 2020c; Fathollahi-Fard et al., 2018; Ghadami et al., 2021; Moosavi et al., 2021). The engineering problems are solved by the application of metaheuristic algorithms based on natural behaviors. Therefore, in the SAA the temperature just is a mathematical character and the physical aspects of it is not considered in present study. Also, through the SAA, the initial temperature factor should be selected based on try and error method with considering to minimum value of the cost function. While, In the present investigation, the temperature in SAA is assumed equal to 120 o^{C} according to Aleksendrić and Carlone (2015) in the similar study.

Equation 3

Mutation Rate ® 0.01
Cross Over Probability ® 0.8
Initial Population ® 50
Number of Iteration ® 50

Equation 4

$$\begin{array}{l}\text{Temperature Update Function } ® \text{ Exponential temperature function}\\ \text{Reannealing Interval } ® \text{ } 100\\ \text{Initial Temperature } ® \text{ } 120\circ^{C}\\ \text{Number of Iteration } ® \text{ } 50\end{array}$$

Equation 5

$$\begin{array}{l}\text{Poll Method } ® \text{ GPS Positive basis N2}\\ \text{Expansion Factor } ® \text{ } 4\\ \text{Mesh Initial Size } ® \text{ } 3\\ \text{Contraction Factor } ® \text{ } 0.5\\ \text{Mesh Tolerance } ® \text{ 1e-6}\end{array}$$

In the last stage of this research, the efficiency of designed reactors based on integration of CCD-RSM and metaheuristic algorithms is evaluated in lab scale setup (Fig. 2) in optimum conditions and in time variation. Also, with the mentioned experimental practices, behavior of reactors is compared by CCD-RSM and GA, PSA and SAA outcomes as prediction systems. Finally, the efficiency of BOD_5 and TSS removal are appraised in three time periods containing 1, 2 and 3 hours according to standard methods for water and wastewater examinations (Gheibi et al. 2021).

3. Result and discussion

In results and discussion section mathematical modelling and experimental practices, managerial insights, sustainability and operational framework are argued.

3.1.Mathematical modelling and experimental practices

Results of PSTs designing in CCD-RSM technique are illustrated in Fig.6, according to the determined experiments in Table 4. It is essential to say that mean flow (Q-Ave), maximum flow (Q Max), cohesion coefficient (K), particles mean diameter (d), particles relative density (S), and runoff coefficient (f) in the intended sewage-treatment plant are sequential as 15000 $m^3. d^{-1}$, 45000 $m^3. d^{-1}$, 0.07, 100 microns, 1.36, 0.028 (Yaseen et al., 2021; Al-Mafraji et al., 2021; Novikov et al., 2021; Leung et al., 2021). According to Fig. 6, f1, f5, f6, and f8 have the most fluctuations through all optimization runs and the standard deviations of them are more than other functions. With consideration to the range of fluctuations, the optimization process is so complex and in the real designing process, the role of integrated CCD-RSM and metaheuristic algorithms is determined more than more. The values in Fig. 6 are normalized in range of 0-1 and the closer these values are to zero, the better results occur.

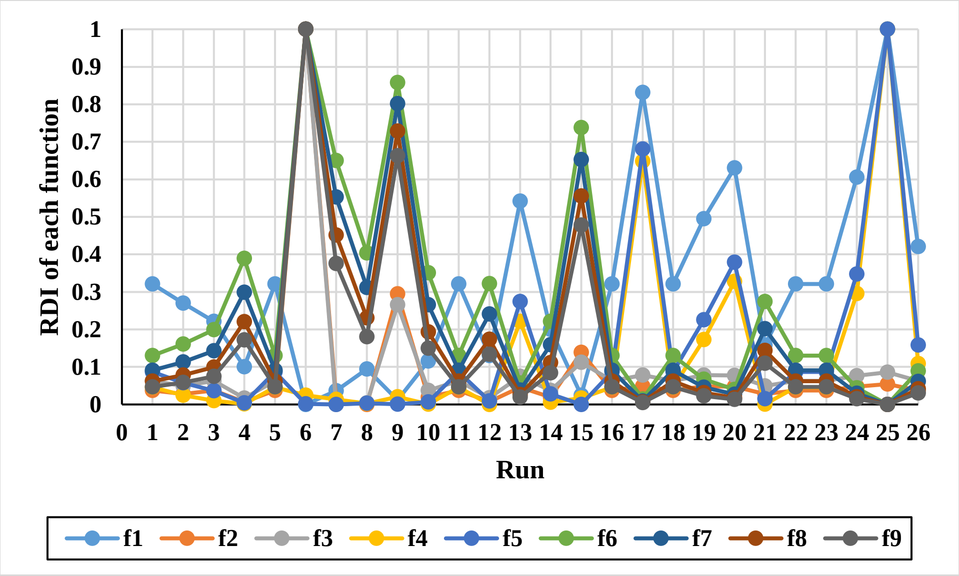


Fig.6. Planned tests' data distribution in PSTs designing.

According to the Fig.6, it is understandable that the quantity of f1-f9 functions is different in each test. These quantities should convert to a response surface according to the scenarios defined in Equation 2 after computations. As the final step, analysis related to each scenario's superposition of nine functions will be evaluated. The product result of function's weight at RDI quantity of each test for economic scenario is shown in Fig.7.

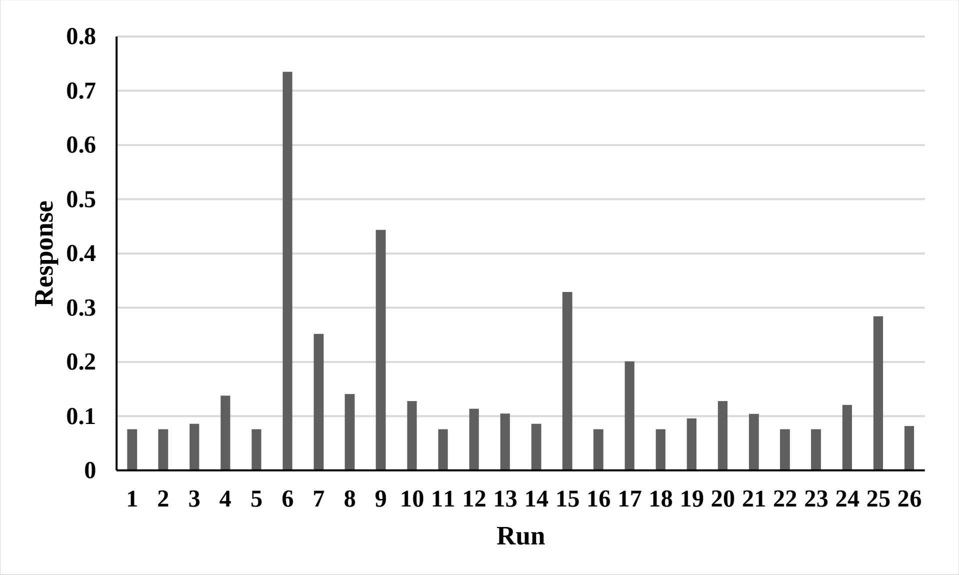


Fig.7. Planned tests' results for PSTs designing in economic scenario.

After the statistical analysis of tests results in the economic scenario, a quadratic model with the regression coefficient of 0.99 obtained to predict the response surface which is shown in the Equation 6. The reduced version of equations according to importance of parameters are presented in the following of each formula.

On the other words, the unnecessary factors are eliminated in the equations and just, high weight parameters are presented. The importance of each term is determined according to their coefficient value as their weights.

Equation 6

Response $= +0.50627 - 0.054971 * n - 0.13047 * W - 0.010069 * L + 0.21522 * H + 0.026489 * SOR + 8.77372E\text{-}003 * n * W + 6.30309E\text{-}004 * n * L - 0.030795 * n * H - 1.51847E\text{-}003 * n * SOR + 4.11796E\text{-}004 * W * L + 5.87990E\text{-}003 * W * H + 3.87429E\text{-}004 * W * SOR - 1.54210E\text{-}004 * L * H - 6.25939E\text{-}005 * L * SOR - 2.14394E\text{-}003 * H * SOR + 0.012270 * n^2 + 1.14781E\text{-}003 * W^2 + 4.08207E\text{-}005 * L^2 - 0.013774 * H^2 - 1.91272E\text{-}004 * SOR^2$

⬇

Response (Reduced form) $= +0.50627 - 0.054971 * n - 0.13047 * W - 0.010069 * L + 0.21522 * H + 0.026489 * SOR - 0.030795 * n * H + 0.012270 * n^2 - 0.013774 * H^2$

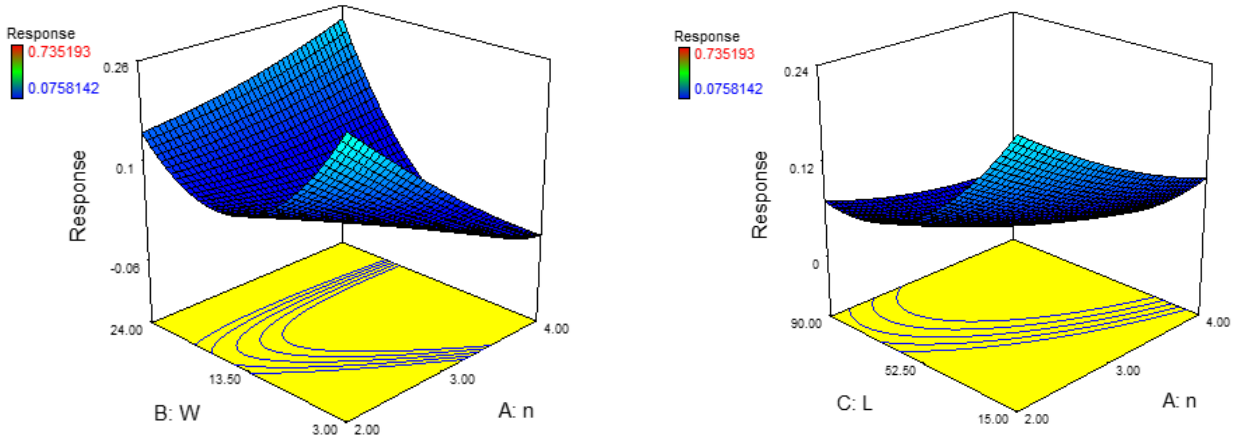
In following, a sensitivity analysis of parameters that influence the designing planned, Analysis of Variance (ANOVA) results of the existing model is demonstrated in Table 5.

Table 5. ANOVA analysis of parameters that influence PSTs design in economic scenario.

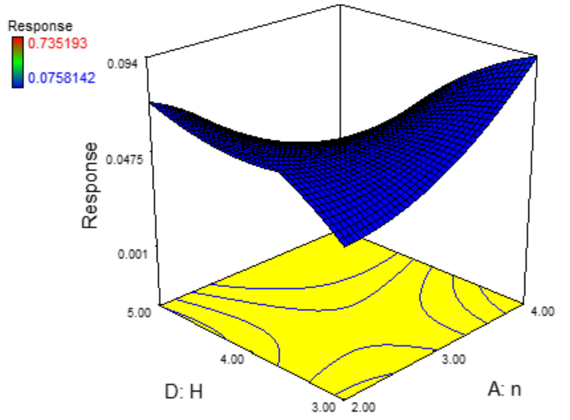
Source	Sum of Squares	df	Mean Square	F Value	p-value (Prob > F)	
Model	0.553132	20	0.027657	51.13501	0.0002	significant
A-n	0.000543	1	0.000543	1.00461	0.3622	-
B-W	0.049756	1	0.049756	91.99425	0.0002	-
C-L	0.008559	1	0.008559	15.82543	0.0106	-
D-H	9.58E-06	1	9.58E-06	0.01772	0.8993	-
E-SOR	0	1	0	0	1.0000	-
AB	0.014814	1	0.014814	27.38977	0.0034	-
AC	0.000975	1	0.000975	1.803066	0.2371	-
AD	0.001655	1	0.001655	3.060622	0.1406	-
AE	0.000402	1	0.000402	0.744139	0.4278	-
BC	0.045891	1	0.045891	84.84907	0.0003	-
BD	0.006653	1	0.006653	12.30158	0.0171	-
BE	0.002889	1	0.002889	5.3408	0.0688	-
CD	5.84E-05	1	5.84E-05	0.107928	0.7558	-
CE	0.000962	1	0.000962	1.778152	0.2399	-
DE	0.000802	1	0.000802	1.483438	0.2776	-
A^2	0.000744	1	0.000744	1.376013	0.2936	-
B^2	0.079162	1	0.079162	146.3649	< 0.0001	-
C^2	0.01629	1	0.01629	30.11829	0.0027	-

D^2	0.000938	1	0.000938	1.733937	0.2450	-
E^2	0.001809	1	0.001809	3.343859	0.1270	-
Residual	0.002704	5	0.000541	-	-	-
Lack of Fit	0.002704	1	0.002704	-	-	-
Pure Error	0	4	0	-	-	-
Cor Total	0.555836	25	-	-	-	-

According to Table 5, it can be concluded that the model's p-value with the amount of 0.0002 has enough validity to predict the response surface. Moreover, the width (W) and length (L) of the PST with the sequential p-value amount of 0.0002 and 0.0106 have the most significant influence on the response surface in economic scenario. In the next step, the tanks number (n) and height of each tank with the sequential p-value of 0.36 and 0.89 have the most influence on the response surface. In conclusion, it is worth noting that the tank's width (W) factor with the p-value amount below 0.005 is the main factor in an economic design. Binary comparison of parameters that influence the response surface is demonstrated in Fig.8. In the parameter’s binary comparison, the more variation gradient of a parameter in contrast to the economic response surface, the more it is valuable in the design. For instance, by seeing slope gradient in the W-n curve, it can understand that the variation of PSTs' width (W) is more severe than the variation of tanks number (n), which shows the importance of W in comparison to n.



(a) (b)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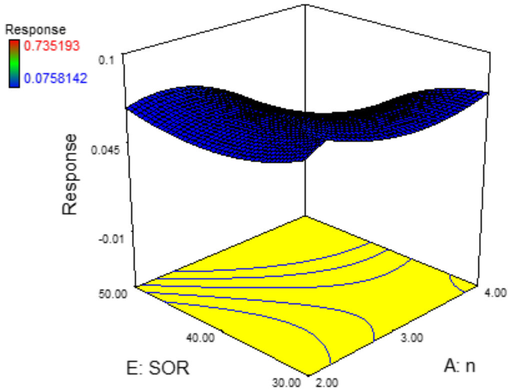
0.094
0.0475
0.001
Response
5.00
4.00
3.00
D: H
2.00
3.00
4.00
A: n

(c)


Response
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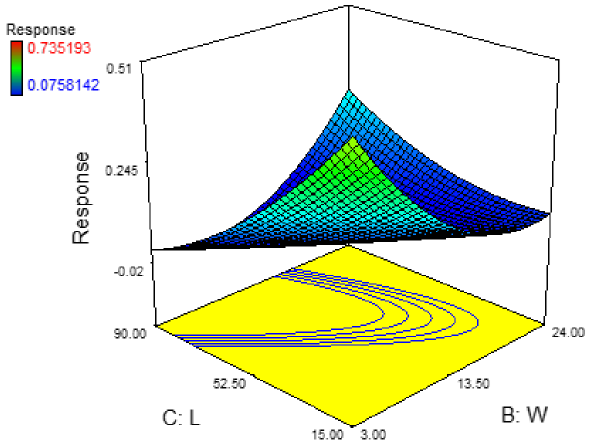
0.0758142
0.1
0.045
-0.01
Response
50.00
40.00
30.00
E: SOR
2.00
3.00
4.00
A: n

(d)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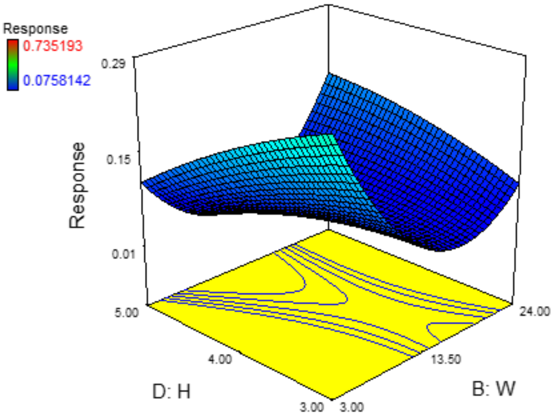
0.0758142
0.51
0.245
-0.02
Response
90.00
52.50
15.00
C: L
3.00
13.50
24.00
B: W

(e)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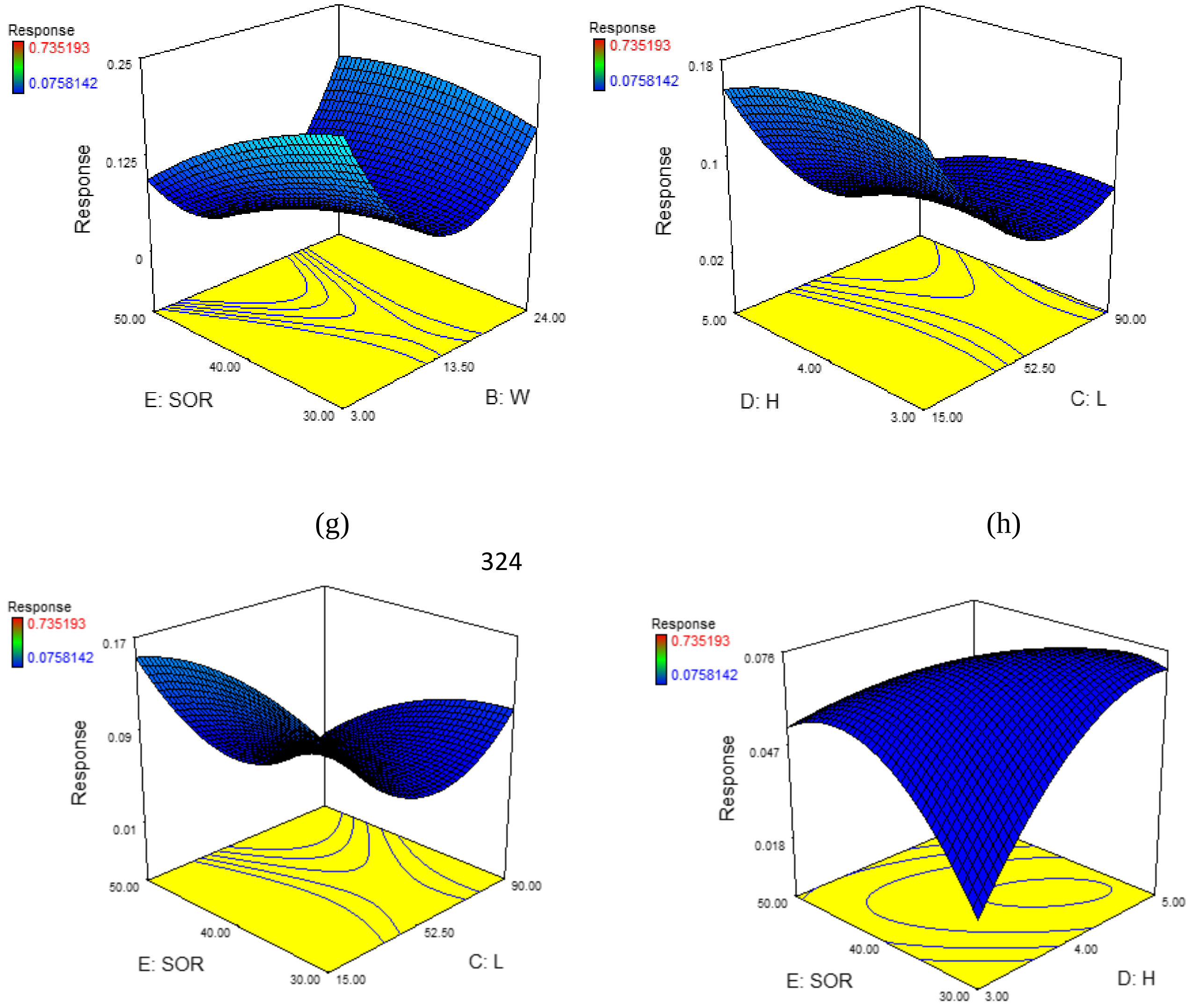
0.29
0.15
0.01
Response
5.00
4.00
3.00
D: H
3.00
13.50
24.00
B: W

(f)



(g) (h)

(i) (j)

Fig.8. Binary sensitivity analysis of parameters which influence on the response surface.

Statistical distribution of CCD-RSM methods test results compared to the normal curve is depicted in Fig.9. It can understand that these tests results are not in the vicinity of the normal curve, which means the abnormal distribution of results in this scenario.

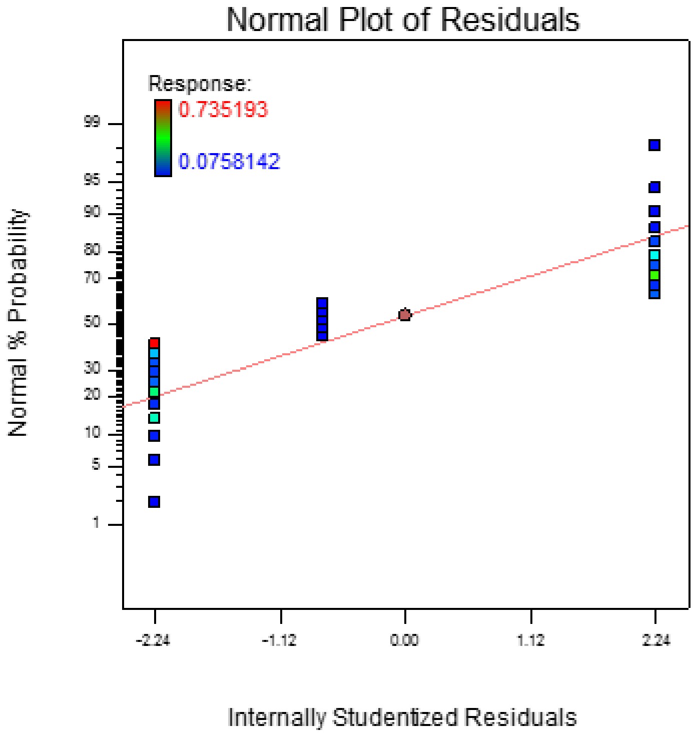
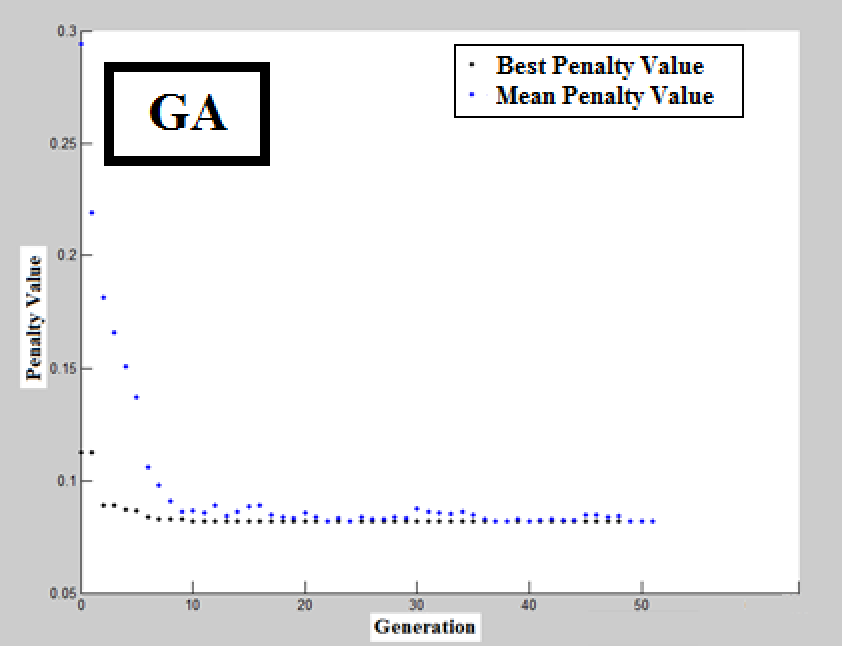


Fig.9. Results distribution of economic scenario's tests in comparison to the normal curve.

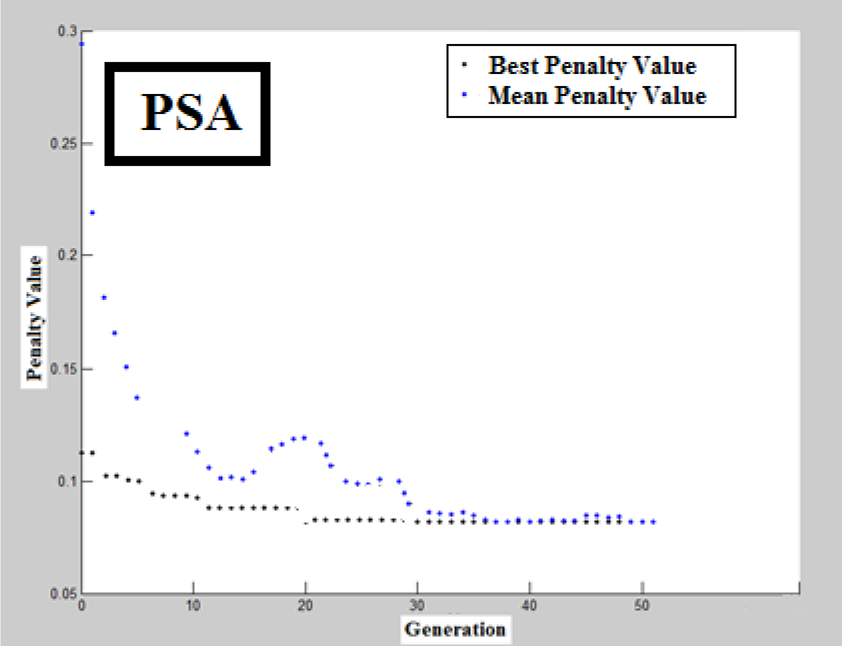
According to Equation 6 in the CCD-RSM method, suggested optimal quantities are shown in Table 6. In the following, to choose a final optimal condition, each of these optimal quantities should be evaluated in the MATLAB programming surface as per GA, PSA and SAA in Fig. 10. As per the mentioned Fig., by application of all metaheuristic algorithms in economic scenario, the amount of cost function (Penalty value) is reduced through the different iterations. But, the PSA struggled to optimize the error function more than others, especially in the last iterations. It is worth noting that the vertical values in range of 0.05-0.3 is equal to error and it is related to summation of all nine cost functions errors (Table 3).

Table 6. Optimal condition suggestions in the CCD-RSM model for designing PSTs in the economic scenario.

Number	**n**	**W**	**L**	**H**	**SOR**	**Response**
1	2.06	14.6	67.65	4.82	48.8	0.073701
2	3.05	21.04	32.22	3.6	34.22	0.00649
3	3.25	22.06	20.07	3.62	43.19	0.053094
4	2.37	14.29	78.11	3.94	33.81	0.072731


GA
Best Penalty Value
Mean Penalty Value
Penalty Value
0.3
0.25
0.2
0.15
0.1
0.05
Generation
0
10
20
30
40
50

(a)


PSA
Best Penalty Value
Mean Penalty Value
Penalty Value
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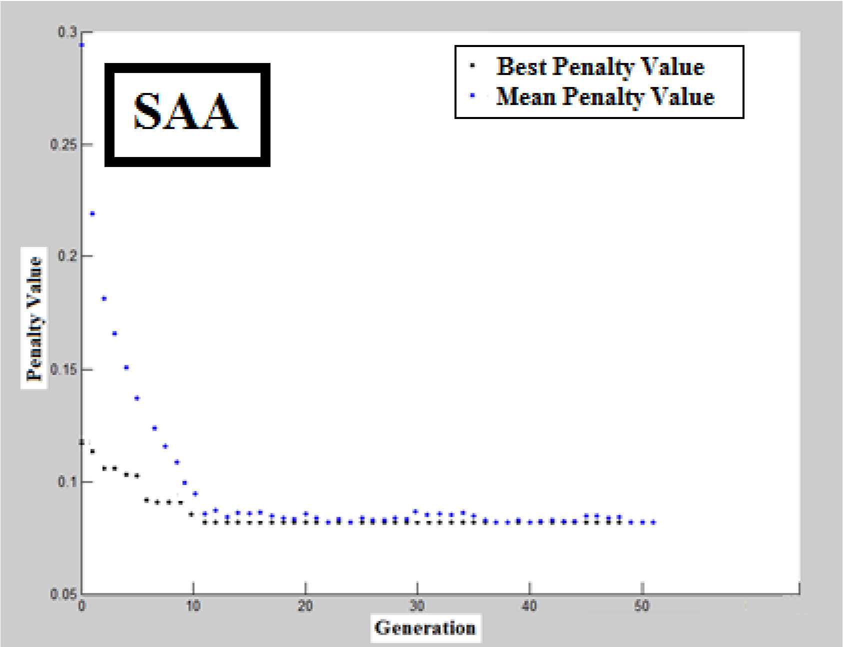
0.25
0.2
0.15
0.1
0.05
Generation
0
10
20
30
40
50

(b)



(c)

Fig.10. Calibrating process in economic scenario with (a) GA, (b) PSA and SAA.

In the followings, the outputs of RSM, GA, PSA and SAA computations are compared with mean experimental outcomes in optimum conditions as per Fig. 11. The declared comparison has been illustrated that PSA algorithm shows the best efficiency in economic scenario with 0.02 mean error value based on Equation 7. Also, in this assessment, all four suggestions are appraised and mean values are presented as an error.

Equation 7

Response = +0.452 - 0.0325*n - 0.142* W - 0.00965* L + 0.2058* H + 0.028526* SOR + 8.0569E-003* n * W + 5.985267E-004* n * L - 0.047152* n * H - 1.98065E-003* n * SOR + 4.230912E-004* W * L + 5.27419E-003* W * H + 3.6236E-004* W * SOR-1.42985E-004* L * H- 6.01782E-005* L * SOR – 1.961045E-003* H * SOR + 0.0295598* n^2 + 0.9517207E-003* W^2+ 6.3595205E – 005* L^2 - 0.012597* H^2 - 1.814036E-004* SOR^2

⬇

Response (Reduced form) = +0.452 - 0.0325*n - 0.142* W - 0.00965* L + 0.2058* H + 0.028526* SOR - 0.047152* n * H + 0.0295598* n^2 - 0.012597* H^2

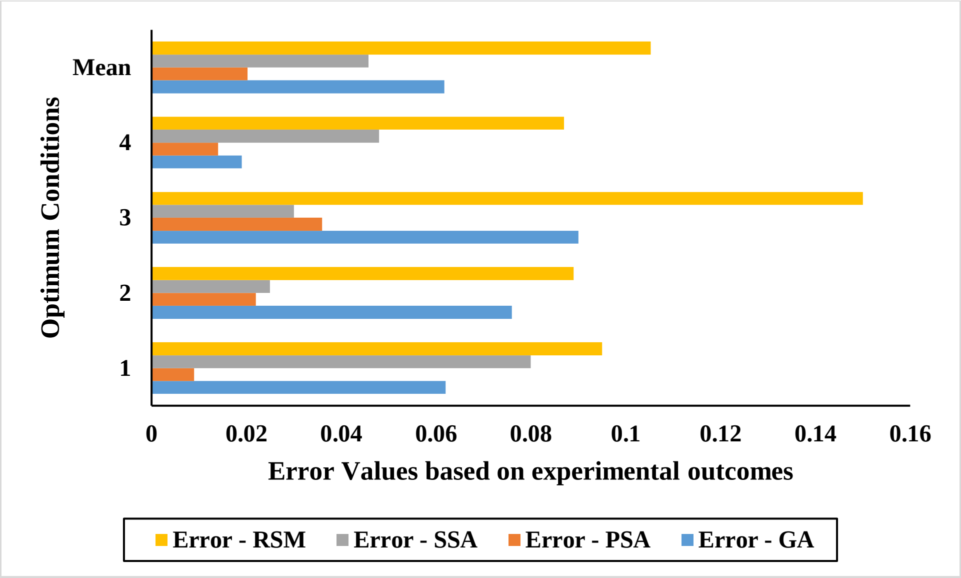


Fig.11. Error values of calibrated Equations in comparison of experimental outcomes in economic scenario.

In improve process scenario, to make simulations' results reach a unique aim, the product of RDI of each function (Equation 2) and its weight (as response surface) is considered in Fig.12.

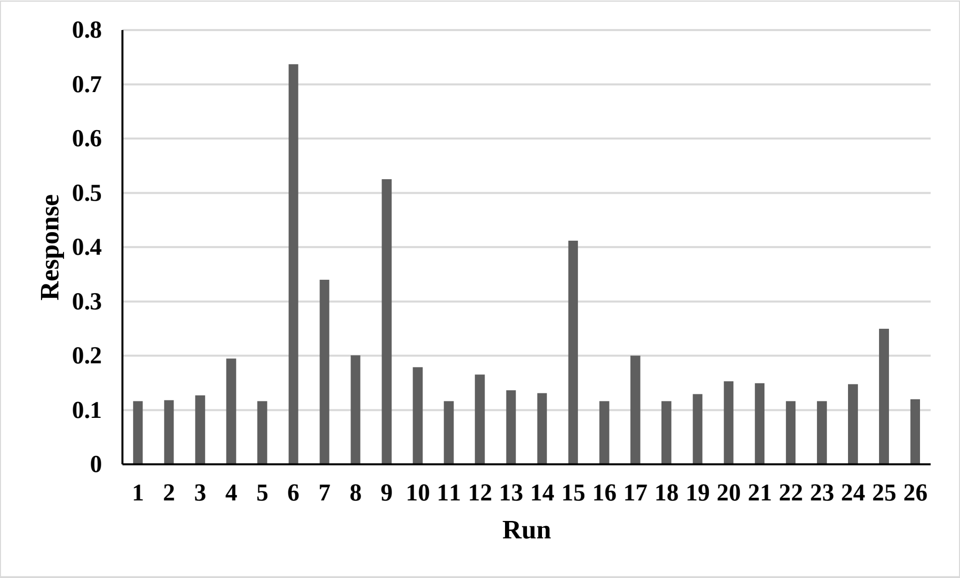


Fig.12. Planned tests' results in designing PSTs in the improve process scenario.

After an integrative evaluation of variable parameters' manner and the response surface, a quadratic model with the regression coefficient of 0.99 determined to predict the response surface, which is shown in the Equation 8.

Equation 8

Response = - 0.23903 + 0.048851* n - 0.12043* W - 8.88844E-003* L + 0.37657* H + 0.039770* SOR+ 7.43581E - 003* n * W + 3.59109E-004* n * L - 0.038342* n * H - 2.13657E-003* n * SOR + 3.79678E-004* W * L + 4.60277E-003* W * H + 3.39347E-004* W * SOR - 3.97741E-

004* L * H - 6.23272E-005* L * SOR - 3.33394E-003* H * SOR + 7.74323E-003* n^2 + 1.16343E-003* W^2 + 4.41420E-005* L^2 - 0.021531* H^2 - 2.66665E-004* SOR^2

⬇

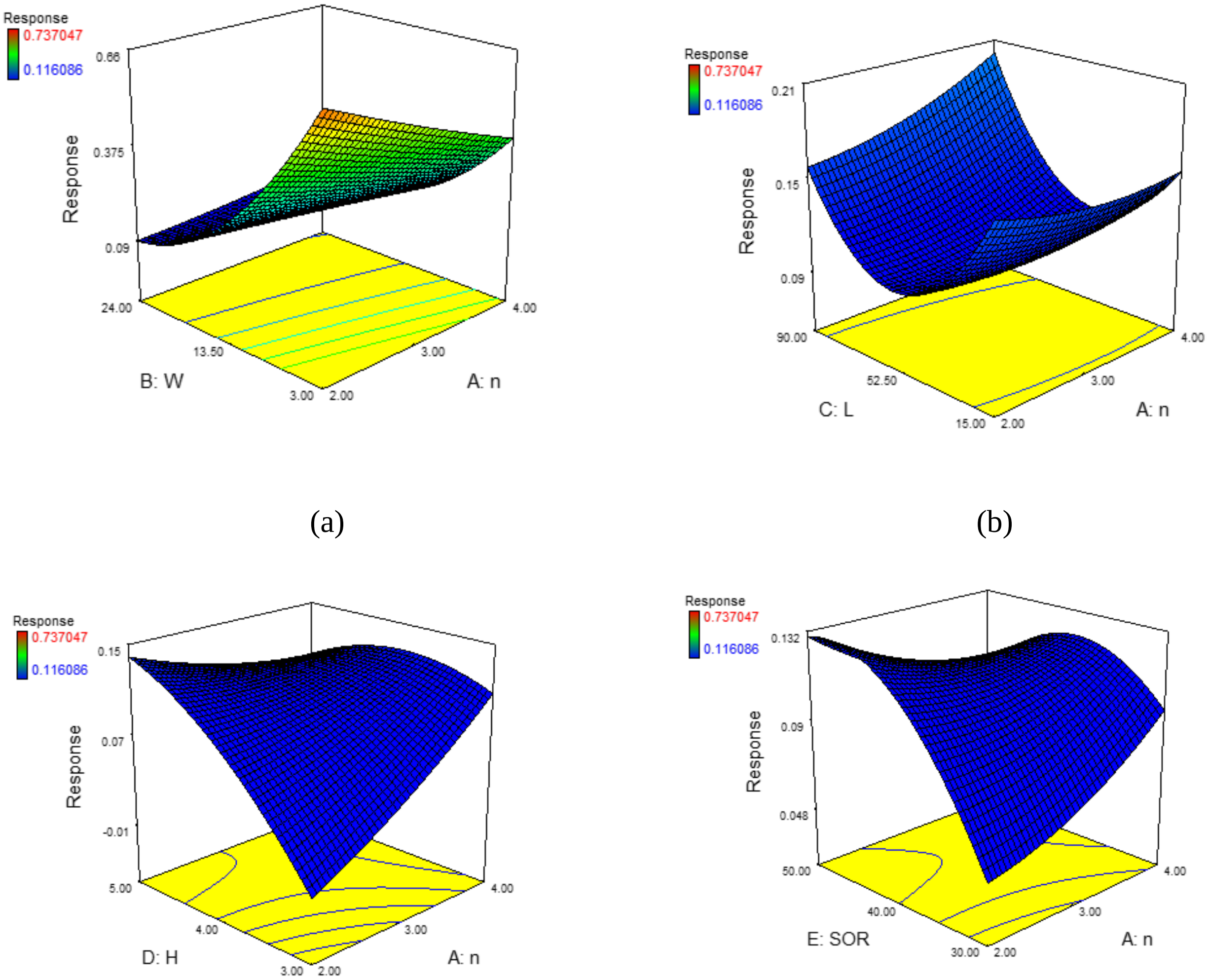
Response (Reduced form) = - 0.23903 + 0.048851* n - 0.12043* W + 0.37657* H + 0.039770* SOR - 0.038342* n * H - 0.021531* H^2

ANOVA results of effective parameters on the response surface are illustrated in Table 6. according to Table 7, the model's P-Value is 0.0009, which is below 0.005 and is assured. Moreover, the width (W) parameter and length (L) of the tank's P-value quantities are sequential 0.0005 and 0.0086, with the least P-Value and most important influence. In the next step, the tank's number (n) and the tank's height (H) are the parameters that influence the response surface. In conclusion, the tank's width (W) parameter has the most influence on the response surface, and this claim was also proved in the economic scenario. Binary sensitivity analysis of effective parameters on the response surface is shown in Fig.13.

Table 7. ANOVA analysis of the effective parameters in PSTs designing in improve process scenario.

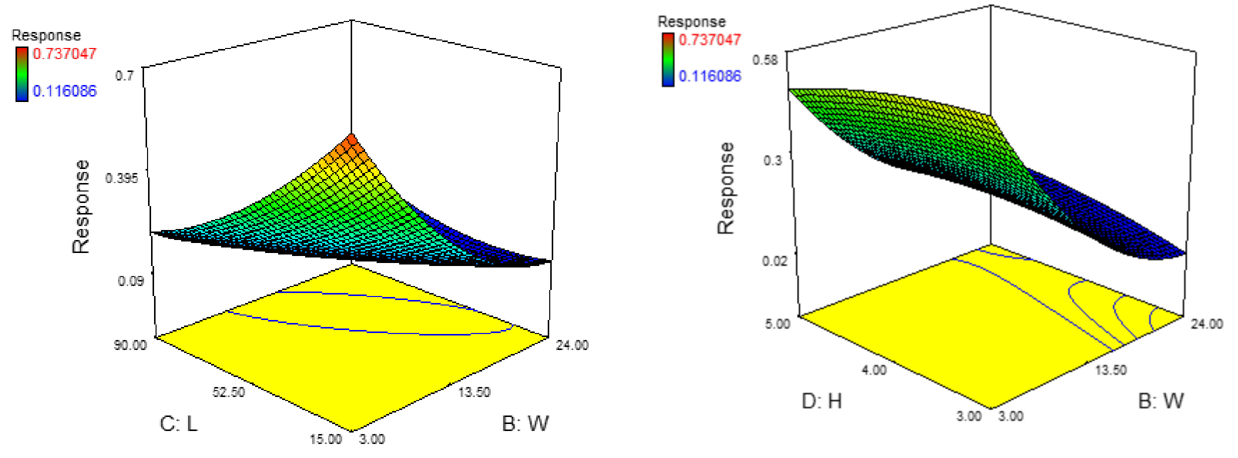
Source	Sum of Squares	df	Mean Square	F Value	p-value (Prob > F)	
Model	0.546902	20	0.027345	26.01187	0.0009	significant
A-n	0.001698	1	0.001698	1.615328	0.2597	-
B-W	0.069473	1	0.069473	66.08564	0.0005	-
C-L	0.018454	1	0.018454	17.55425	0.0086	-
D-H	2.27E-05	1	2.27E-05	0.0216	0.8889	-
E-SOR	0	1	0	0	1.0000	-
AB	0.01064	1	0.01064	10.12163	0.0245	-
AC	0.000317	1	0.000317	0.301114	0.6068	-
AD	0.002566	1	0.002566	2.440943	0.1790	-
AE	0.000797	1	0.000797	0.757969	0.4238	-
BC	0.039012	1	0.039012	37.10962	0.0017	-
BD	0.004077	1	0.004077	3.878221	0.1060	-
BE	0.002216	1	0.002216	2.10806	0.2062	-
CD	0.000388	1	0.000388	0.369384	0.5699	-
CE	0.000954	1	0.000954	0.907054	0.3846	-
DE	0.00194	1	0.00194	1.84557	0.2324	-
A^2	0.000296	1	0.000296	0.281943	0.6182	-
B^2	0.081332	1	0.081332	77.36645	0.0003	-
C^2	0.019048	1	0.019048	18.11943	0.0080	-
D^2	0.002292	1	0.002292	2.180025	0.1998	-
E^2	0.003515	1	0.003515	3.343859	0.1270	-
Residual	0.005256	5	0.001051	-	-	-
Lack of Fit	0.005256	1	0.005256	-	-	-

Pure Error	0	4	0	-	-	-
Cor Total	0.552158	25	-	-	-	-

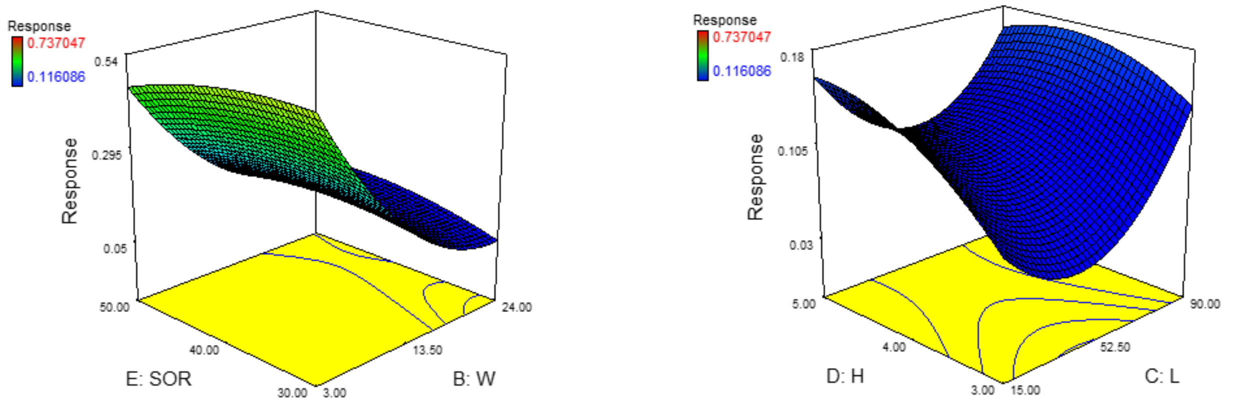


(a) (b)

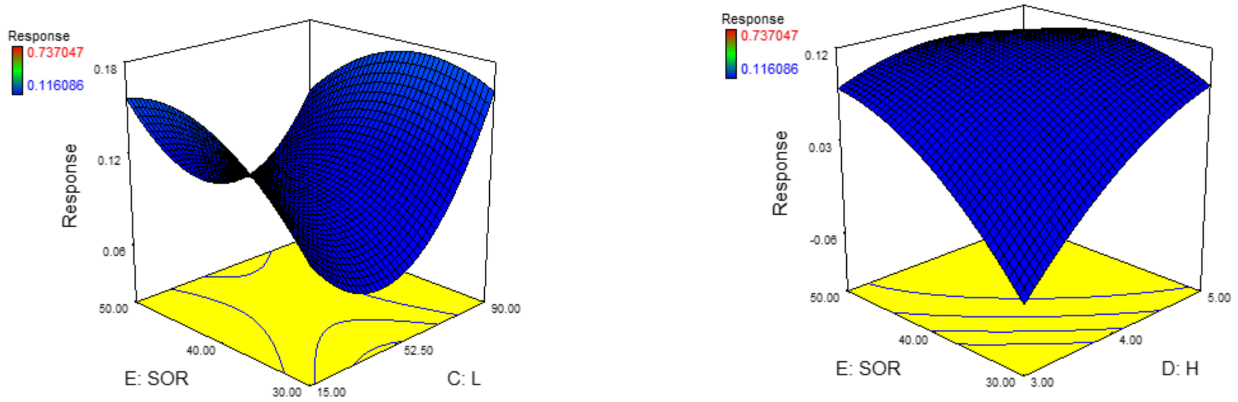
(c) (d)



(e) (f)



(g) (h)



(I) (g)

Fig.13. Binary sensitivity analysis of effective parameters on the response surface in improve process scenario.

The normalization analysis of tests' results in improving process scenarios depicts that products are not near the normal line like economic scenario, which means the distribution of the results is abnormal. Statistical distribution of tests' outcomes in the CCD-RSM method is reported in Fig.14.

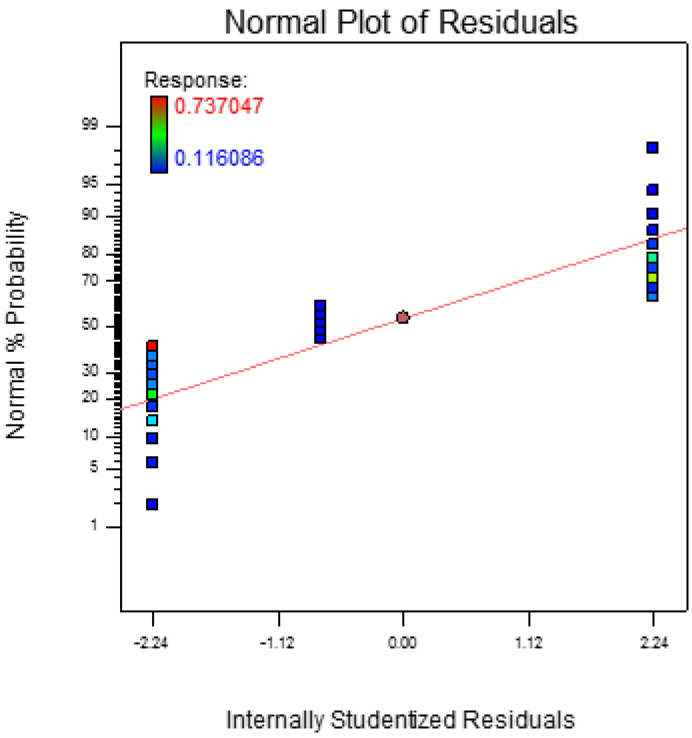
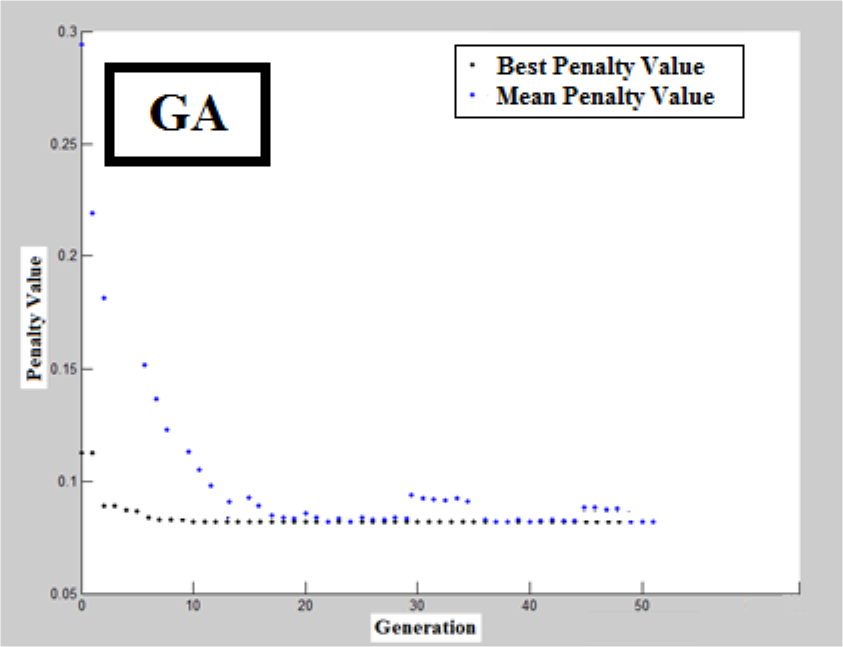


Fig.14. Improve process scenario tests' results distribution compare to the normal curve.

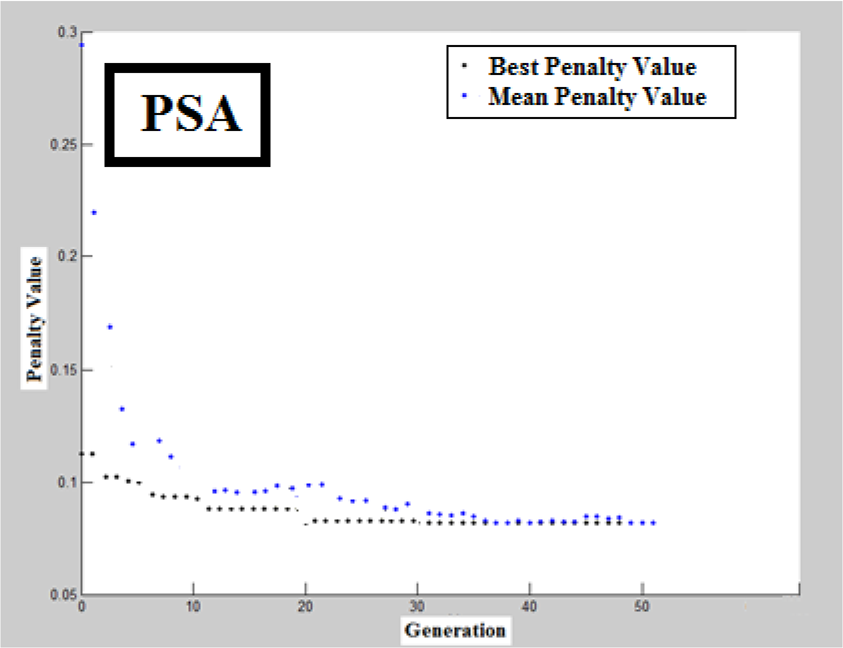
Optimal results suggested by the CCD-RSM method to minimize the response surface is demonstrated in Table 8. These suggestions should be re-evaluated during the designing process to obtain a final-optimal model. Optimization procedure of improving process scenario in three GA, PSA and SAA computations is illustrated in Fig. 15. In the following, calibrated Equations' error in comparison of experimental values in optimum suggestions based on GA, PSA, SAA and CCD-RSM are summarized in Fig. 16. Likewise, all improving process responses are computed in each method and then, they are appraised with experimental outcomes according to simple absolute distance percentage.

Table 8. optimal modes predictions in the CCD-RSM method for designing PSTs in improve process scenario.

Number	n	W	L	H	SOR	Response
1	3.46	20.75	33.5	4.51	35.57	0.104175
2	2.64	17.02	36.99	3.35	36.68	0.076028
3	3.09	16.1	66.36	4.28	42.13	0.095557
4	2.08	18.62	57.7	3.96	40.34	0.084805


GA
Best Penalty Value
Mean Penalty Value
Penalty Value
0.3
0.25
0.2
0.15
0.1
0.05
0
10
20
30
40
50
Generation

(a)


PSA
Best Penalty Value
Mean Penalty Value
Penalty Value
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0.2
0.15
0.1
0.05
0
10
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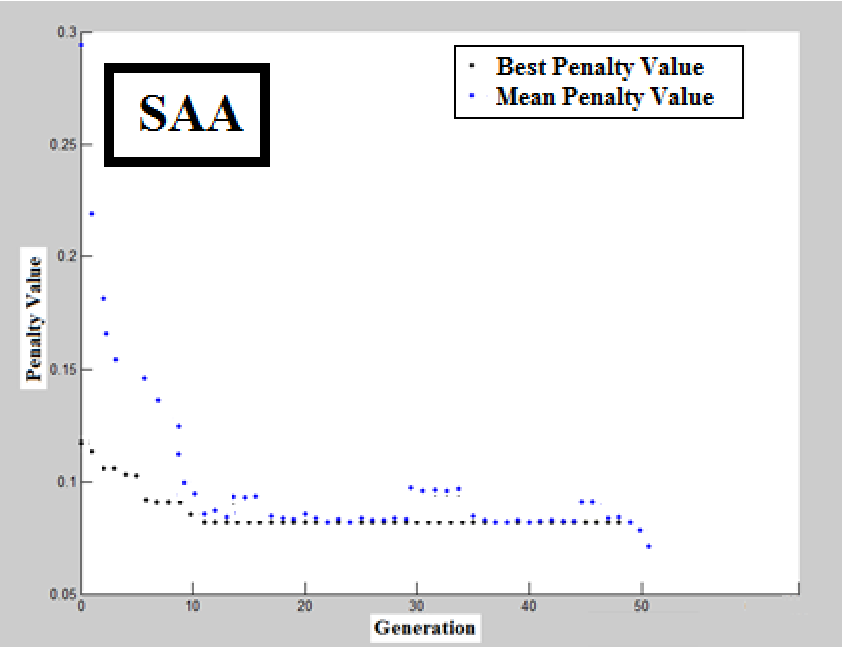
30
40
50
Generation

(b)



(c)

Fig.15. Calibrating process in improving process scenario with (a) GA, (b) PSA and SAA.

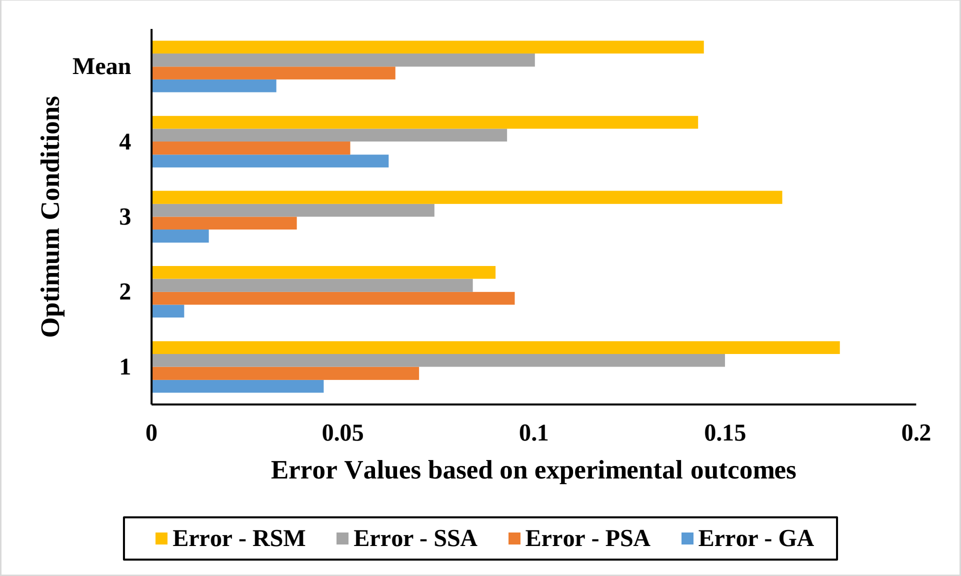


Fig.16. Error values of calibrated Equations in comparison of experimental outcomes in improving process scenario.

As per Fig. 15, in improving process scenario, GA algorithm with 0.032 mean error through all four suggestions results was the best estimation which is illustrated in Equation 9. Likewise, based on Fig. 15, the value of penalty is reduced in different iteration, but, the performance of GA and SAA are more than PSA in improving process scenario which are converged to optimal amount in the minimum time. Besides, with consideration to Fig. 16, performance of GA is better than SAA in error value aspect.

Equation 9

Response $= - 0.205622 + 0.033258 * n - 0.145098 * W - 8.50288E\text{-}003 * L + 0.462102 * H + 0.052378 * SOR + 6.952036E - 003 * n * W + 3.59109E\text{-}004 * n * L - 0.038342 * n * H - 2.13657E\text{-}003 * n * SOR + 3.6352E\text{-}004 * W * L + 2.14025E\text{-}003 * W * H + 1.59362E\text{-}004 * W * SOR - 7.05899E\text{-}004 * L * H - 4.1033052E\text{-}005 * L * SOR - 5.40025E\text{-}003 * H * SOR + 5.3287403E\text{-}003 * n^2 + 3.562188E\text{-}003 * W^2 + 5.62189E\text{-}005 * L^2 - 0.00985601 * H^2 - 3.25665E004 * SOR^2$

⬇

Response (Reduced form) $= - 0.205622 + 0.033258 * n - 0.145098 * W + 0.462102 * H + 0.052378 * SOR - 0.038342 * n * H - 0.00985601 * H^2$

In tank efficiency scenario, the product of nine objective function's RDI with their weights quantities as per CCD-RSM computations in this scenario for each test is shown in Fig.17.

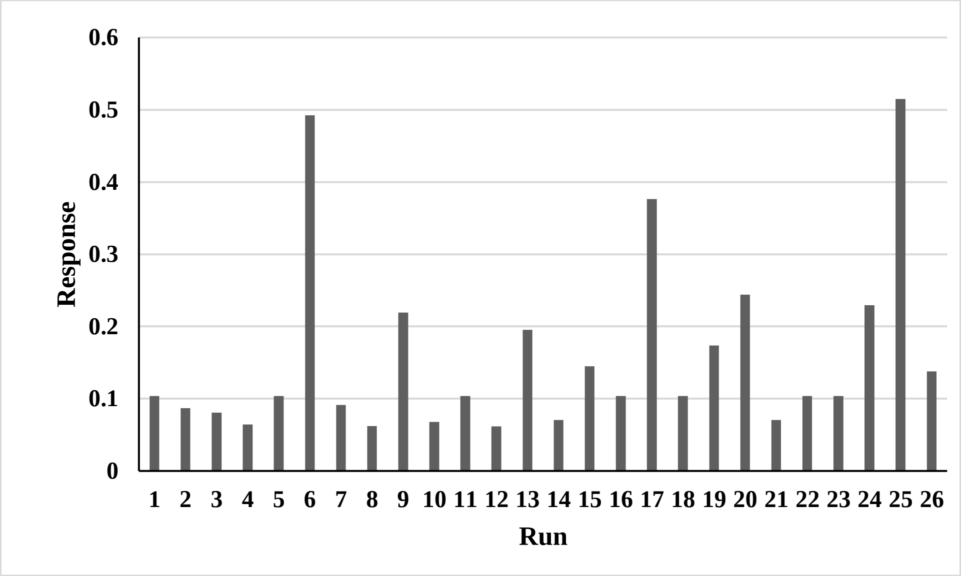
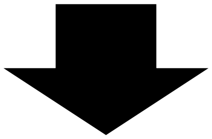


Fig.17. Planned tests' results for designing PSTs in the tank efficiency scenario.

Statistical evaluation of input data into the CCD-RSM model and calculating the response surface (Tank efficiency scenario) in each test has done. The results concluded a quadratic model for predicting the response surface that is demonstrated in Equation 10.

Equation 10

Response $= + 1.31914 - 0.030572 * n - 0.11141 * W - 0.011485 * L - 0.085569 * H - 5.69808E\text{-}003 * SOR + 7.76851E - 003 * n * W + 7.90049E\text{-}004 * n * L - 0.024440 * n * H - 5.53472E\text{-}004 * n * SOR + 4.49553E\text{-}004 * W * L + 7.20194E\text{-}003 * W * H + 4.24728E\text{-}004 * W * SOR + 6.51613E\text{-}004 * L * H - 8.43560E - 006 * L * SOR + 2.17595E\text{-}003 * H * SOR + 9.79504E\text{-}003 * n^2 + 7.28836E\text{-}004 * W^2 + 2.19976E\text{-}005 * L^2 - 4.47826E\text{-}003 * H^2 - 8.29530E\text{-}005 * SOR^2$



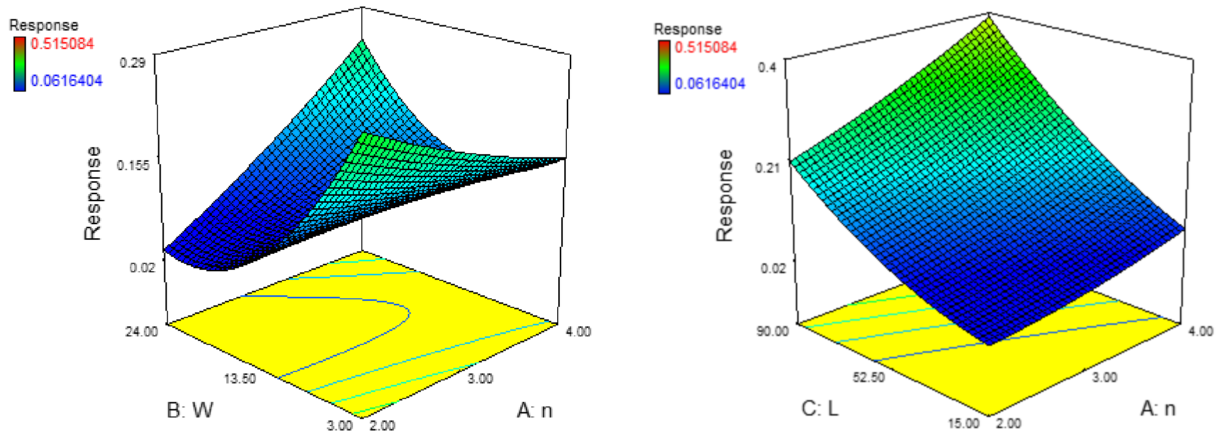
Response (Reduced form) = + 1.31914 - 0.030572* n - 0.11141* W - 0.011485* L - 0.085569* H + 7.90049E-004* n * L - 0.024440* n * H

ANOVA results and sensitivity evaluation of effective parameters on the response surface in the tank efficiency scenario is reported in Table 9. Results show that Equation four's computational model's P-Value is below 0.0001 and is assured of predicting and optimizing. Moreover, the length (L) and the tank's number (n) factors with the sequential P-Value of 0.0002 and 0.0003 significantly influence the design. After them, the tank's height (H) and the tank's width (W) impact the response surface substantially. While in the economic scenario and the improve process scenario, the width (W) had a significant impact. At the same time, in all three scenarios, geometrical indicators have a very considerable influence on the response surface. Sensitivity analysis and binary analysis of effective parameters on the response surface in the tank efficiency scenario is shown in Fig.18.

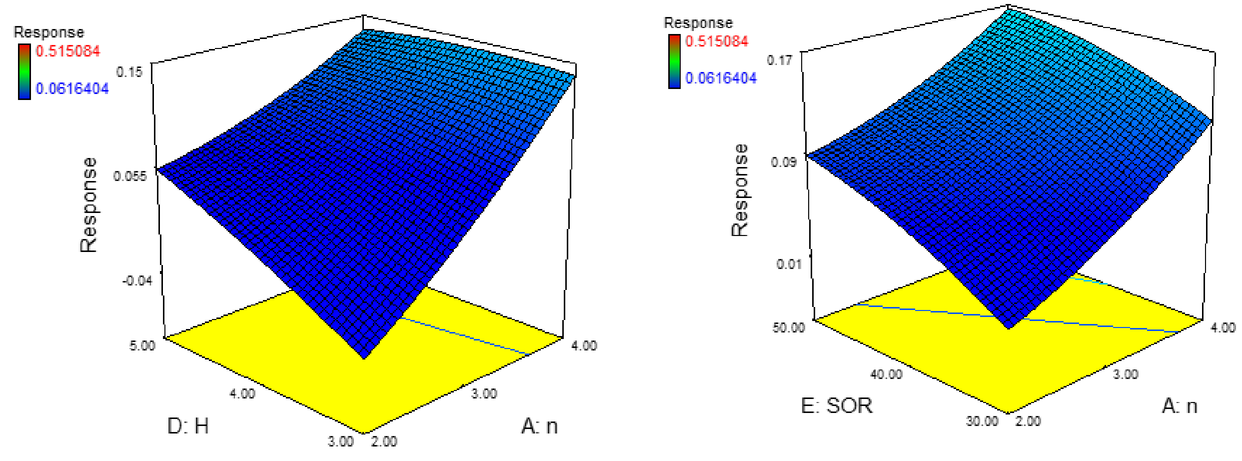
Table 9. ANOVA evaluation of effective parameters on the PSTs design in the tank efficiency scenario.

Source	Sum of Squares	df	Mean Square	F Value	p-value (Prob > F)	
Model	0.391476	20	0.019574	192.413	< 0.0001	significant
A-n	0.008602	1	0.008602	84.55746	0.0003	-
B-W	0.0003	1	0.0003	2.946611	0.1467	-
C-L	0.009511	1	0.009511	93.49107	0.0002	-
D-H	0.001626	1	0.001626	15.98114	0.0103	-
E-SOR	0	1	0	0	1.0000	-
AB	0.011614	1	0.011614	114.1658	0.0001	-
AC	0.001532	1	0.001532	15.06099	0.0116	-
AD	0.001043	1	0.001043	10.24911	0.0240	-
AE	5.35E-05	1	5.35E-05	0.525622	0.5009	-
BC	0.054692	1	0.054692	537.632	< 0.0001	-
BD	0.009982	1	0.009982	98.1206	0.0002	-
BE	0.003472	1	0.003472	34.12573	0.0021	-
CD	0.001042	1	0.001042	10.24529	0.0240	-
CE	1.75E-05	1	1.75E-05	0.171703	0.6958	-
DE	0.000826	1	0.000826	8.124171	0.0358	-
A^2	0.000474	1	0.000474	4.66225	0.0833	-
B^2	0.031918	1	0.031918	313.7623	< 0.0001	-
C^2	0.00473	1	0.00473	46.50066	0.0010	-
D^2	9.91E-05	1	9.91E-05	0.974545	0.3689	-
E^2	0.00034	1	0.00034	3.343859	0.1270	-

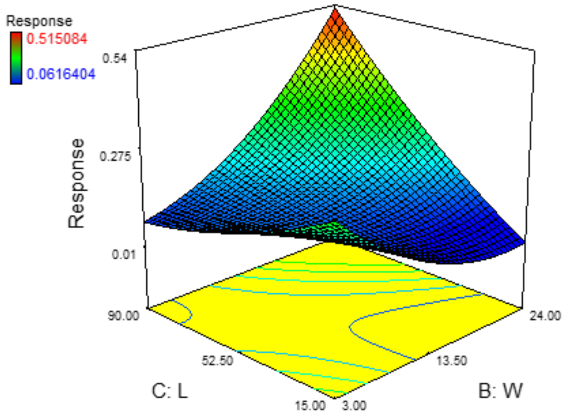
Residual	0.000509	5	0.000102	-	-	-
Lack of Fit	0.000509	1	0.000509	-	-	-
Pure Error	0	4	0	-	-	-
Cor Total	0.391984	25	-	-	-	-



(a) (b)



(c) (d)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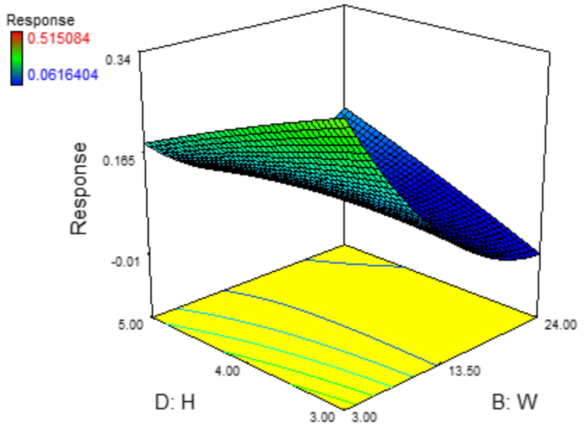
0.0616404
0.54
0.275
0.01
Response
90.00
52.50
15.00
C: L
3.00
13.50
24.00
B: W

(e)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0.34
0.165
-0.01
Response
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3.00
D: H
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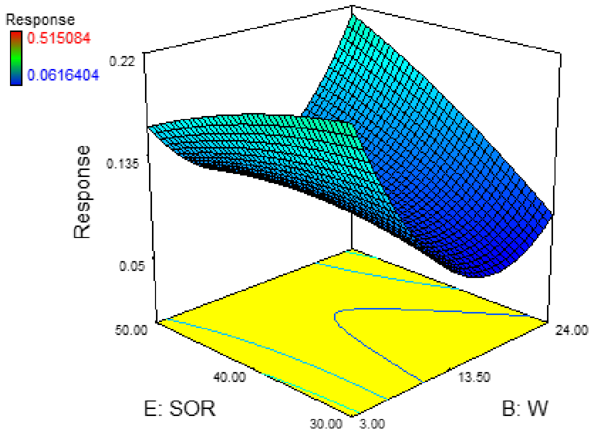
13.50
24.00
B: W

(f)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0.135
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Response
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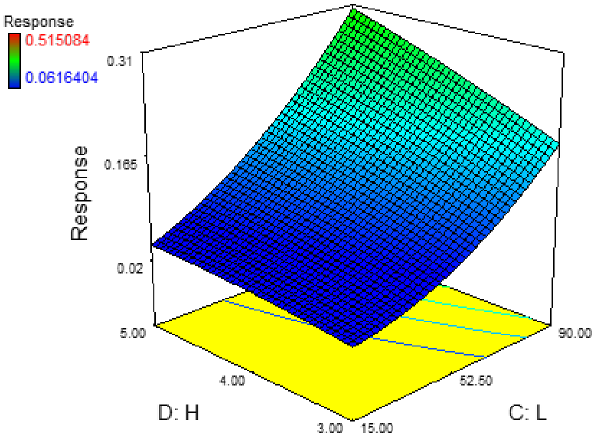
30.00
E: SOR
3.00
13.50
24.00
B: W

(g)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3.00
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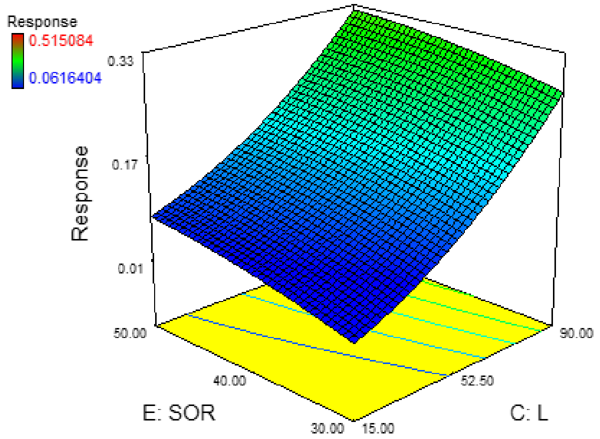
52.50
90.00
C: L

(h)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Response
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30.00
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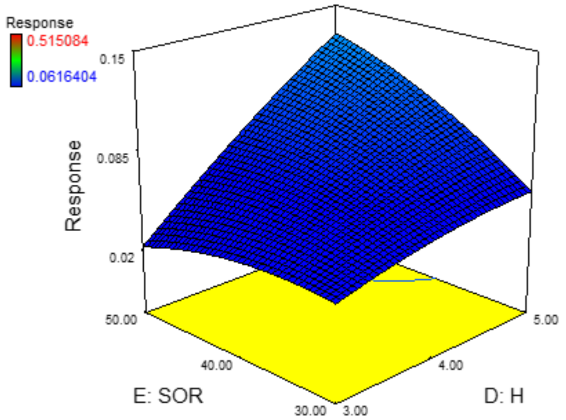
15.00
52.50
90.00
C: L

(i)


Response
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0.0616404
0.15
0.085
0.02
Response
50.00
40.00
30.00
E: SOR
3.00
4.00
5.00
D: H

(j)

Fig.18. Binary sensitivity analysis of effective parameters on the response surface in the tank efficiency scenario in designing PSTs.

Planned tests response surface distributions in the CCD-RSM method evaluated for being normal, and the results show the abnormal distribution of output data like both previous scenarios. Statistical data dispersion and comparing them with the normal line is manifested in Fig.19.

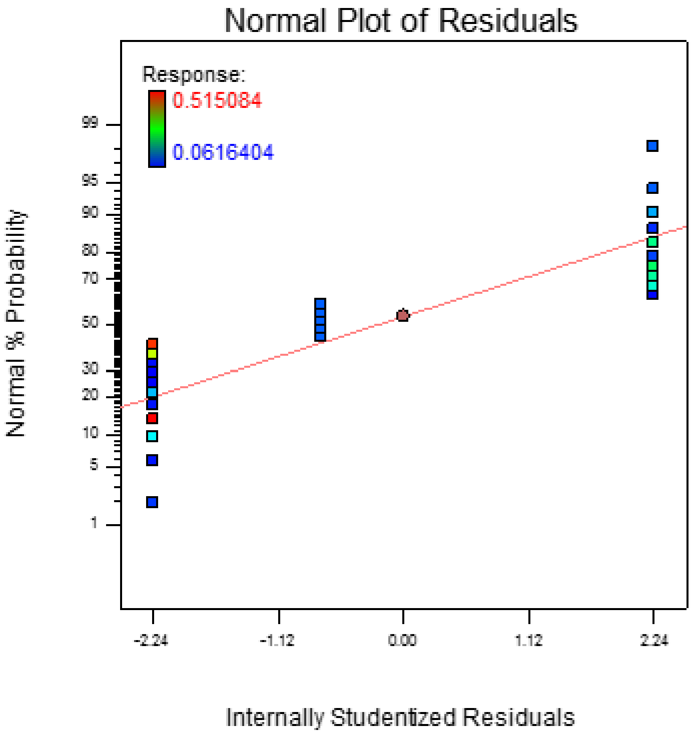
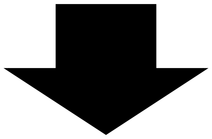


Fig.19. tests' results' distribution in the tank efficiency scenario comparing to the normal line.

At the end of the statistical modelling, the CCD-RSM method's optimal mode suggestions for minimizing the response surface in the tank efficiency scenario is reported in Table 10. In the following optimization of computed Equation in tank efficiency scenario in different iterations are presented according to Fig.20. Also, the error amount of GA, PSA, SAA and CCD-RSM computations are illustrated based on Fig. 21. According to mentioned Fig., the PSA evolutionary algorithm can enhance accuracy of Equation in comparison of other ones with 0.063 through all four optimum suggestions in tank efficiency scenario (Equation 11). Plus, in the tank efficiency scenario, PSA and SAA are converged to the best solution in the minimum iterations, but, from error value aspect, PSA has the best efficiency for prediction of response (Figs. 20 and 21).

Equation 11

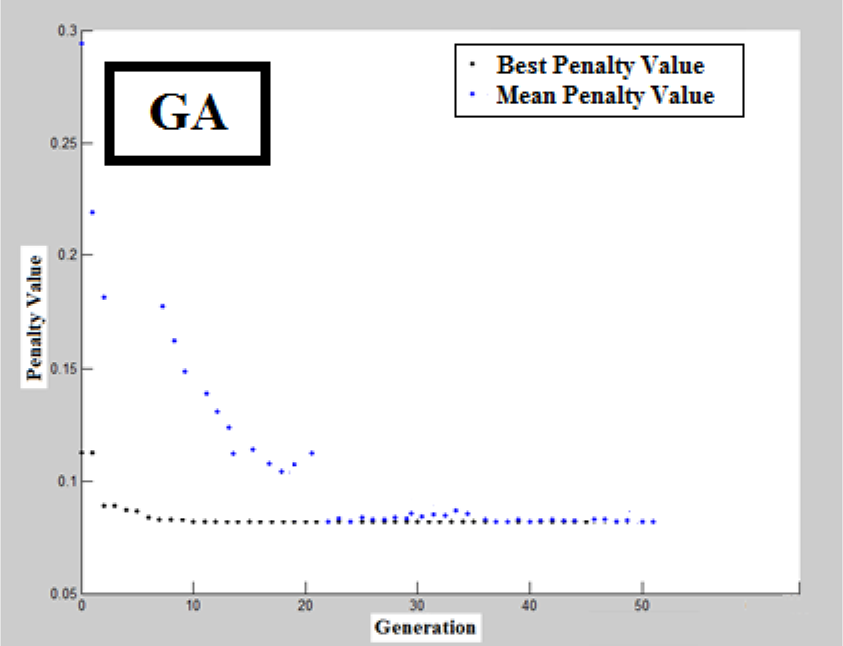
Response = $+ 1.31914 - 0.030572 * n - 0.11141 * W - 0.011485 * L - 0.085569 * H - 5.69808E\text{-}003 * SOR + 7.76851E - 003 * n * W + 7.90049E\text{-}004 * n * L - 0.024440 * n * H - 5.53472E\text{-}004 * n * SOR + 4.49553E\text{-}004 * W * L + 7.20194E\text{-}003 * W * H + 4.24728E\text{-}004 * W * SOR + 6.51613E\text{-}004 * L * H - 8.43560E - 006 * L * SOR + 2.17595E\text{-}003 * H * SOR + 9.79504E\text{-}003 * n^2 + 7.28836E\text{-}004 * W^2 + 2.19976E\text{-}005 * L^2 - 4.47826E\text{-}003 * H^2 - 8.29530E\text{-}005 * SOR^2$



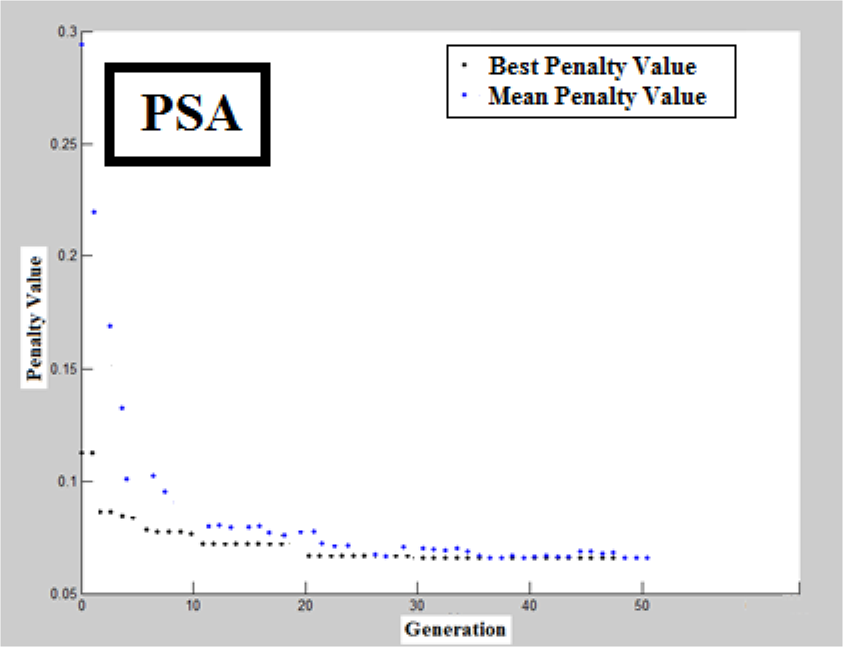
Response (Reduced form) = + 1.31914 - 0.030572* n - 0.11141* W - 0.011485* L - 0.085569* H - 0.024440* n * H

Table 10. The CCD-RSM optimal mode suggestions for designing PSTs in tank efficiency scenario.

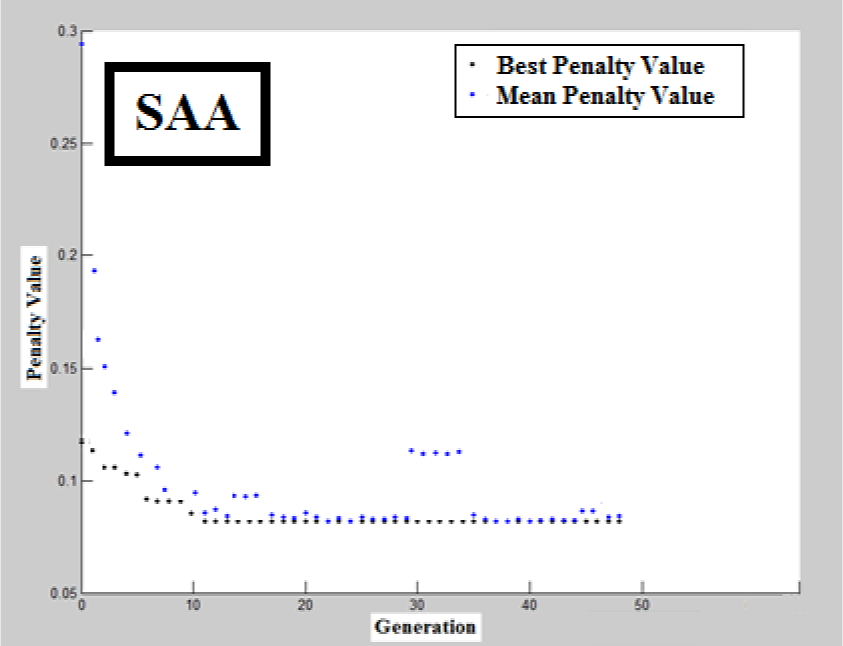
Number	n	W	L	H	SOR	Response
1	2.12	15.9	33.27	4.73	35.39	0.04924
2	2.06	17.31	65.07	3.09	44.43	0.009294
3	3.61	3.67	88.45	4.36	49.77	0.042443
4	2.57	19.72	24.96	3.81	41.82	0.002108



(a)



(b)



(c)

Fig.20. Calibrating process in tank efficiency scenario with (a) GA, (b) PSA and SAA.

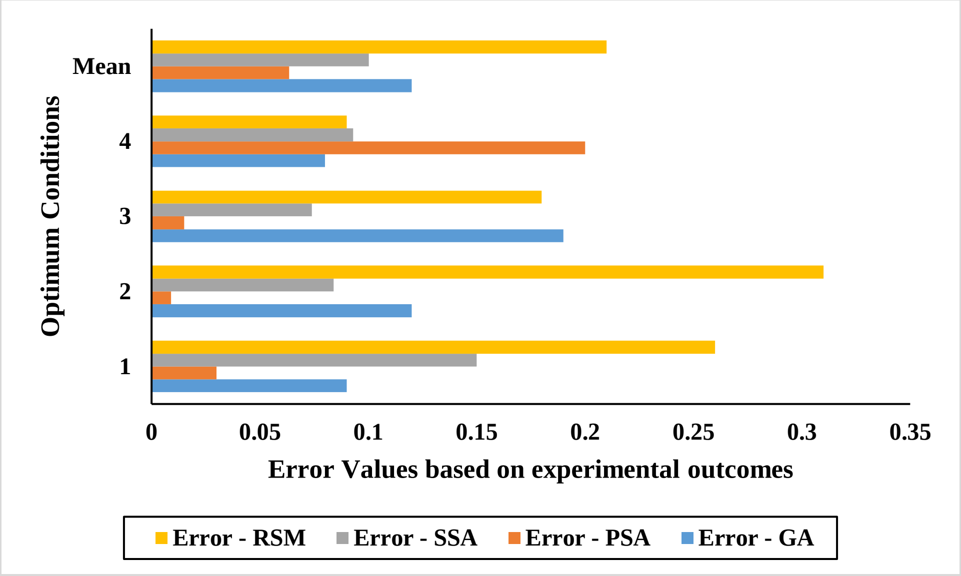


Fig.21. Error values of calibrated Equations in comparison of experimental outcomes in tank efficiency scenario.

At the end of each modelling in three scenarios, suggestions to minimize the response surface was determined as per CCD-RSM. In this section, that suggestions will be evaluated to find one specific optimal model for each scenario. The CCD-RSM model's suggestions for the economic scenario are again evaluated in a programming surface to design PSTs. In the mentioned Scenario, the results of the objective functions are demonstrated in Fig.22 and Fig.23. The function values in the declared Figs are pure amounts of error functions and they have not any physical meaning.

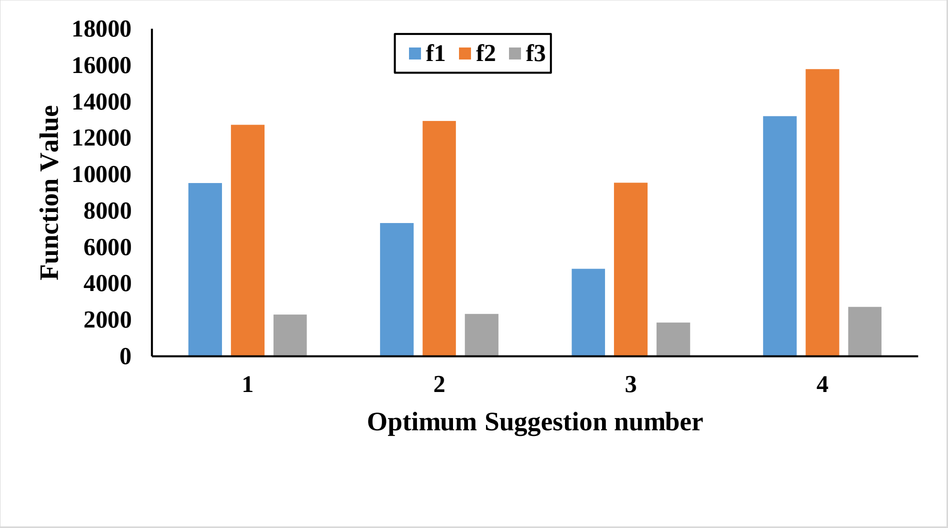


Fig.22. Evaluation of the optimal model in economic scenario as per CCD-RSM (f1-f3).

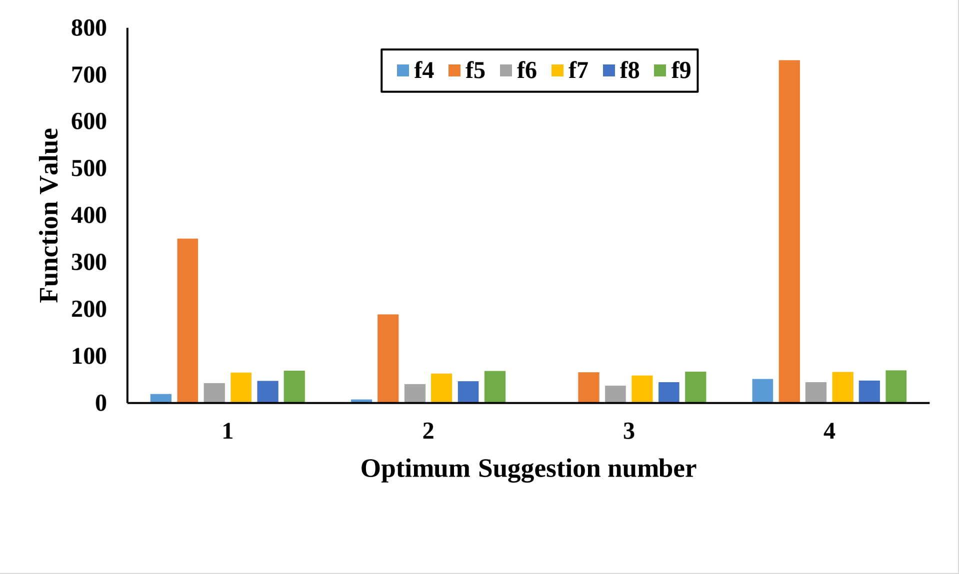


Fig.22. Evaluation of the optimal model in economic scenario as per CCD-RSM (f4-f9).

According to Fig. 22 and 23, the economic function (f1) earned a little weight in the third suggestion, because on its importance in economic scenario. Meanwhile, f2-f5 functions gained little importance in the third suggestion with more weight value. But it is necessary to say that the desirability of f6-f9 procedures is in maximizing the organized data. But in the third suggestion, shown in Table 6, f6-f9 functions are minimized, which means they have less desirability than the other offers in the tank efficiency scenario's indicator. But because of the importance of the economic terms, the number of tanks (n), width (W), length (L), height (H), and the SOR parameters are sequentially chosen as 3, 22m, 20m, 3.5m, and 45 $m^3.m^{-2}.\ d^{-1}$ in the mentioned planning.

Suggested optimal conditions in the CCD-RSM model based on improve process scenario, shown in Table 8, has been evaluated. The results of objective functions for the improve process scenario are shown in Fig. 24 and 25.

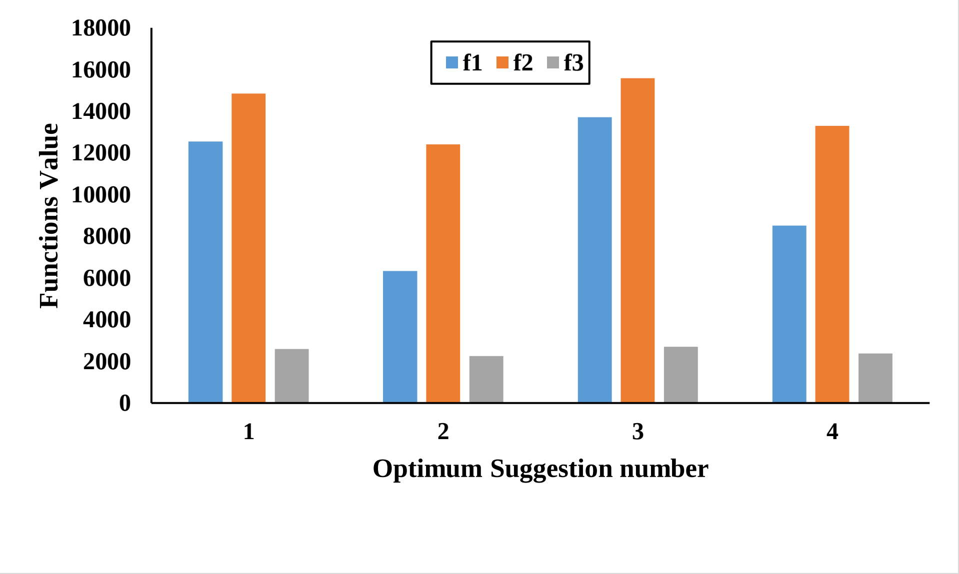


Fig.24. Evaluation of the optimal model in improve process scenario as per CCD-RSM (f1-f3).

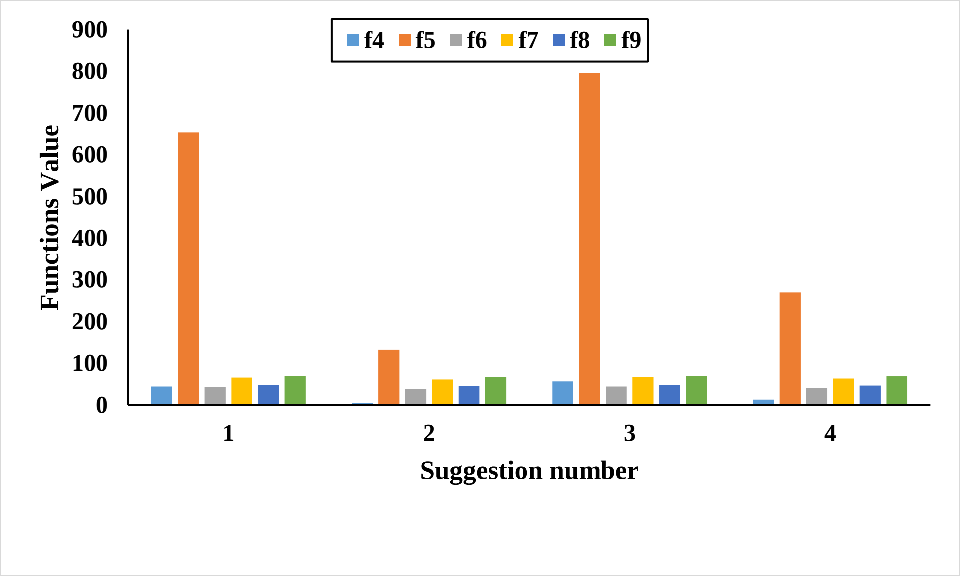


Fig.25. Evaluation of the optimal model in improve process scenario as per CCD-RSM (f4-f9).

In the improve process scenario, the f2-f5 objective functions should be minimized compared to the other suggestions. In the second suggestion, f2-f5 functions are in the minimum condition, which means the most desirability in the improve process scenario. In sum, in the improve process scenario, the optimal mode of the number of tanks (n), width (W), length (L), height (H), and the SOR factors are sequentially taken as 3, 17m, 37m, 3.5m, 36 $m^3.m^{-2}. d^{-1}$.

In the tank efficiency scenario, the suggestion of the CCD-RSM model assessed again. The evaluation of these suggestions through nine objective functions are shown in Fig. 26 and 27.

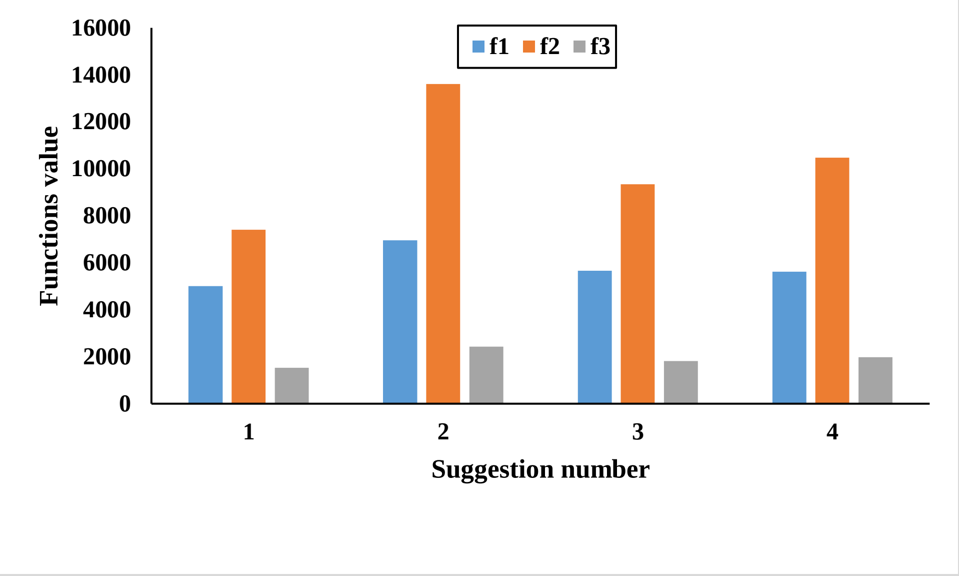


Fig.26. Evaluation of the optimal model in tank efficiency scenario as per CCD-RSM (f1-f3).

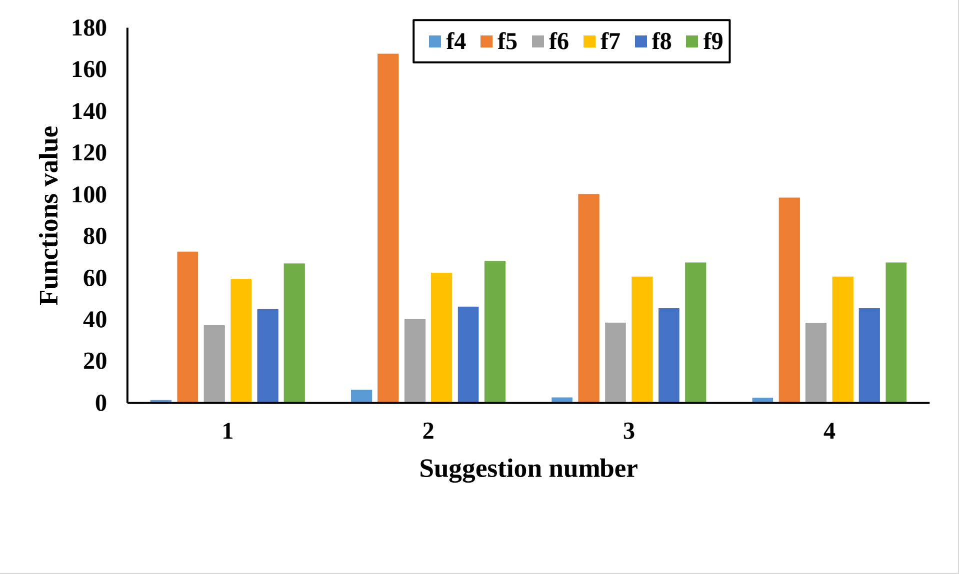
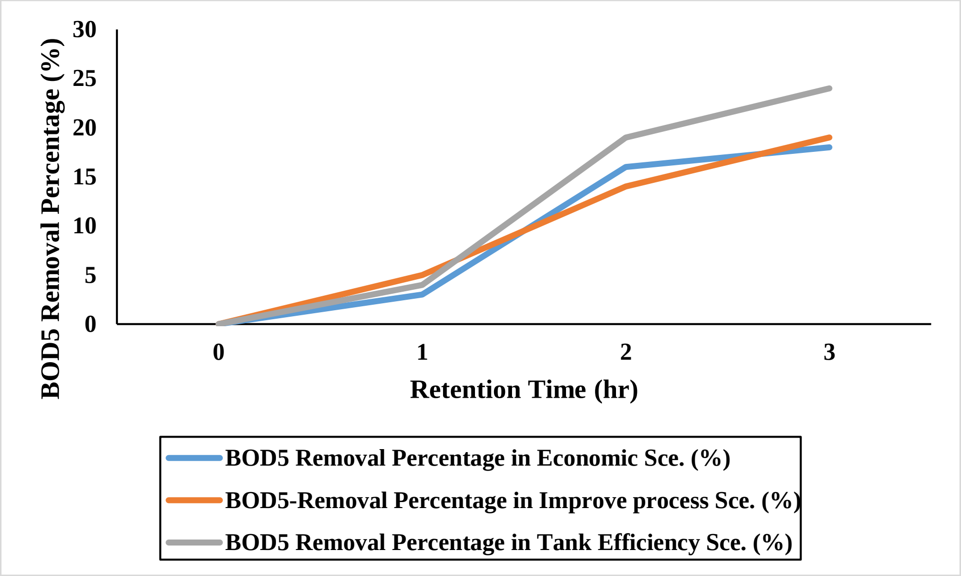


Fig.27. Evaluation of the optimal model in tank efficiency scenario as per CCD-RSM (f4-f9).

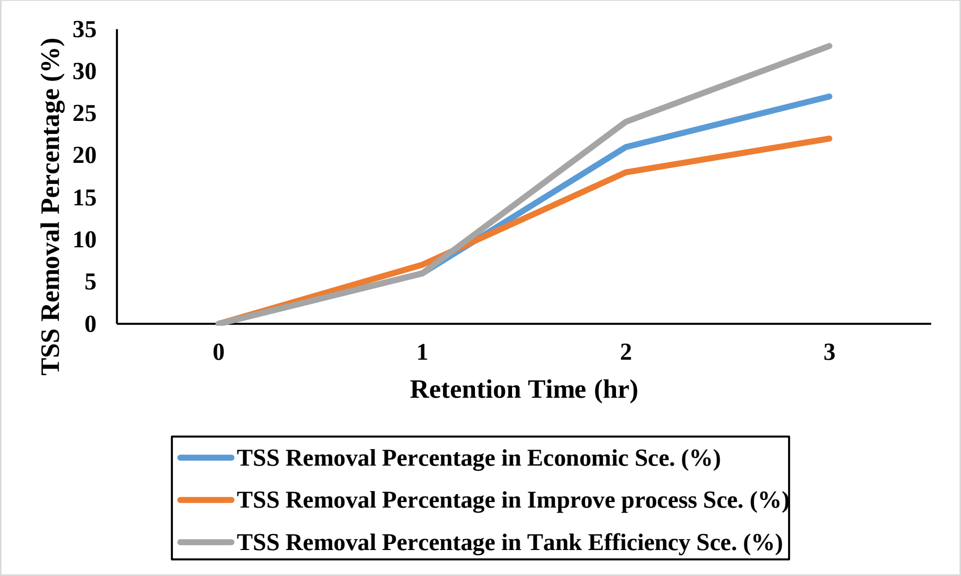
In the tank efficiency scenario, an appropriate situation occurs when the f6-f9 objective functions are minimum. As shown in Fig. 26 and 27, variation of f6-f9 functions in all four suggestions are close to each other. In this situation, choosing the optimal mode should be based on the f1-f5 objective functions. All the f1-f5 functions are in the type of minimized functions that have the most desirability in the first optimal suggestion. In conclusion, the optimal mode of the number of tanks (n), width (W), length (L), height (H), and the SOR parameters are sequentially chosen as 2, 16m, 33m, 4.5m, and 35 $m^3.m^{-2}.\ d^{-1}$.

In the last section of study, the efficiency of BOD_5 and TSS removal from optimum conditions in each scenario are appraised with experimental practices through the time according to Fig. 28. According to mentioned Fig., in tank efficiency scenario, BOD_5 and TSS removal are more than other scenarios and also, it is seen that 2-hour RT is the best values for pollution removal from reactor with considering to both BOD_5

and TSS decontamination. By the outcomes of Fig. 28, around 15% of BOD5 and 20% of TSS are removed in the designed reactors which illustrates appropriate efficiency.



(a)



(b)

Fig.28. Retention Time evaluation with focusing on (a) BOD_5 and (b) TSS elimination.

Yaseen. et al. (2021) have evaluated sedimentation process in wastewater treatment plant with considering experimental practices with and without a baffle. The mentioned investigation results that with baffles, the efficiency of TSS removal is increased about 34%. Also, they place the baffles based on reactor's length and depth (Yaseen et al., 2021). In the other same research, Al-Mafraji et al. (2021) have appraised the efficiency of upper and lower baffles on the PST's performance. In the mentioned study, role of both upper and lower baffles can be illustrated for damping suspended solids based on hydrodynamic computations

(Al-Mafraji et al., 2021). Therefore, evaluation of baffle's design with combination of RSM and evolutionary algorithm can be assumed as future research item.

Novikov et al. (2021) have expressed that with injecting finely bubbles in PST, efficiency of the reactors can be enhanced around 10% (Novikov et al., 2021). Thus, for future researches, optimizing the spraying and aeration processes in PSTs by RSM and metaheuristic can be beneficial. Likewise, based on a research item by Leung et al. (2021), application of Cable Driven Parallel Robot (CDPR) for implementation of lamella tank can promote performance of PSTs (Leung et al., 2021). So, it can be optimized with RSM and meta-heuristic computation as a future research issue.

3.2. Managerial insights

Reengineering process is so important for from managerial aspects and it is necessary among operation the wastewater treatment plants. According to Fig. 29, after sensitive analysis of PSTs based on physical specifications, the speed of problem tracking in the mentioned reactors will be simplified. Then, after reengineering decision, the optimum values can be determined by integrated CCD-RSM and metaheuristic computations as designing environmental supply chain (Chouhan et al., 2021; Mosallanezhad et al., 2021; Fasihi et al., 2021; Akbarpour et al., 2021; Zahedi et al., 2021). Whereas, by kinetic evaluation of pollution elimination in the designed reactors, operation of wastewater treatment plant can be organized. Finally, with the achieved outputs, four stages of PDCA include Plan, Do, Control, and Act are implemented through the reengineering procedure (Sadri et al., 2021; Hamdi-Asl et al., 2021; Fasihi et al., 2021).

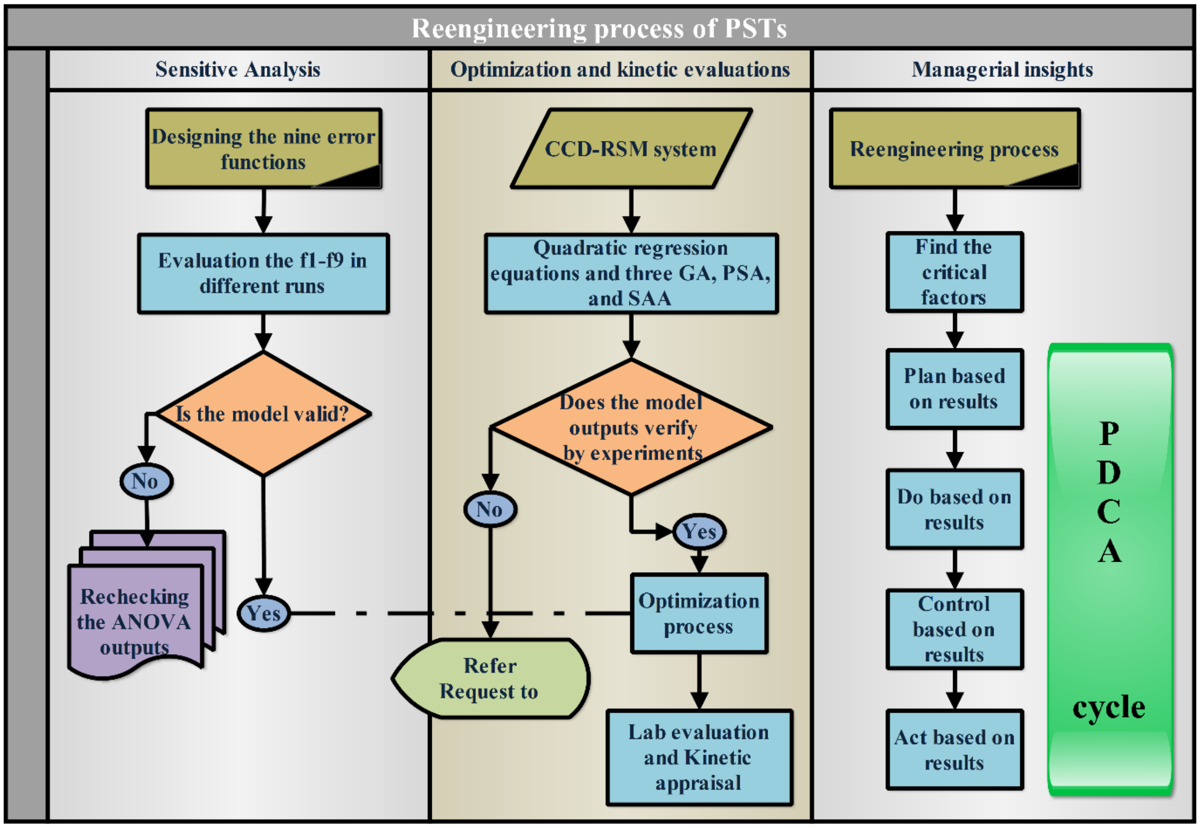


Fig.29. The conceptual model of PSTs reengineering in the present investigation.

3.3. Sustainability

The approach of Sustainable Development Goals (SDGs) through the present study as reengineering approach is illustrated in Fig. 30. Based on the mentioned Fig., three sections of SDGs include Good Health and Well-being (Hosseini et al., 2021), Clean Water and Sanitation (Mousavi et al., 2021), and Sustainable Cities and Communities (Salehi-Amiri et al., 2022) are met. With increasing the quality of wastewater treatment process, both Clean Water and Sanitation and Good Health and Well-being goals are satisfied (). Likewise, the suitable reengineering causes the cost optimization with increasing the efficiency and it is directed to Sustainable Cities and Communities (Mosallanezhad et al., 2021). Therefore, the results of present study can be met the SDGs in the industrial wastewater treatment plants and by the mentioned outputs, the threaten of decontamination process can be converted to opportunity (Fathollahi-Fard et al., 2021).

Fig. 30. The conceptual model of sustainability through the present study.

3.4. Operational framework

With consideration to outcomes of this study, a conditional framework is presented in different situations as per Fig. 31. This created framework shows that through the reengineering the PSTs, different scenarios can be implemented and finally, the superposition of all computations in all scenarios is expressed as per Fig. 31. Based on the results, in each scenario and according to its priorities, a design pattern is suggested. Besides, the mean value of the effective parameters is introduced as the middle level of design factors which satisfies all different scenarios.

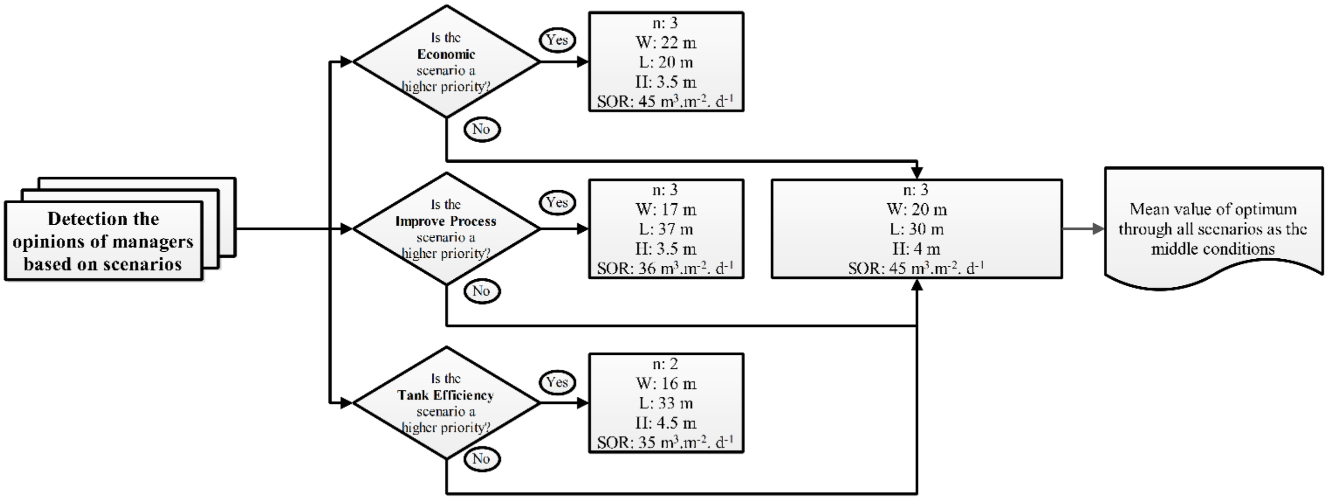


Fig.31. The conditional operational framework for PSTs through this research.

4. Conclusion

PSTs have essential role for elimination of fixed and volatile suspended solids in wastewater treatment plants. With appropriate designing PST, considerable volume of contaminations can be treated and then, operation of biological/chemical process will be easier. In the classical designing methods, all scheming parameters are adjusted by try and error in sequential computations loops. In this study, a novel concept for designing and reengineering PSTs based on combination of RSM, metaheuristic, SBM and experimental efforts is presented. In the first step, computations of PST's are done and the algorithm of design is created. Then, the design of experiments is implemented in CCD-RSM as per computational efforts. In the next step, all CCD-RSM computations are operated in three scenarios containing economic, improve process and tank efficiency with considering to RDI scale less system. Finally, the mentioned prediction Equations are calibrated by GA, PSA and SAA as efficient metaheuristics and they are compared with experimental outcomes for choosing the best metaheuristic algorithm in each scenario. At the end of research, after computing objective functions in all scenarios, BOD_5 and TSS removal are appraised through different RT values.

The main outcomes of this research are including:

- Having a comparison among the proposed metaheuristics, PSA, GA and PSA achieved the minimum error equal to 0.02, 0.032 and 0.063 in comparison of experimental tests for economic, improve process and tank efficiency scenarios, correspondingly, through four CCD-RSM optimum suggestions.

- According to CCD-RSM evaluations, the most effective parameters for economic, improve process and tank efficiency scenarios are including W, W and L with 0.0002, 0.0005 and 0.0002 P-Values, respectively.
- In the economic scenario, the optimum number of tanks (n), width (W), length (L), height (H), and the SOR are equal to 3, 22m, 20m, 3.5m, and 45 $m^3.m^{-2}. d^{-1}$, respectively.
- In the improve process scenario, the optimum number of tanks (n), width (W), length (L), height (H), and the SOR are equal to 3, 17m, 37m, 3.5m, 36 $m^3.m^{-2}. d^{-1}$, respectively.
- In the tank efficiency scenario, the optimum number of tanks (n), width (W), length (L), height (H), and the SOR are equal to 2, 16m, 33m, 4.5m, and 35 $m^3.m^{-2}. d^{-1}$, respectively.
- According to BOD_5 and TSS elimination appraisal during different RT, it can be seen that optimum RT is equal to 2 hr.

At last but not least, the main future research direction is to apply other metaheuristics especially novel metaheuristics like red deer algorithm (Fathollahi-Fard et al., 2020c) and social engineering optimizer (Fathollahi-Fard et al., 2018) and Keshtel algorithm (Fathollahi-Fard et al., 2021) etc.

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