Constructing a smart framework for supplying the biogas energy in green buildings using an integration of response surface methodology, artificial intelligence and petri net modelling

Constructing a novel smart framework for supplying biogas energy in green buildings using an integration of response surface methodology, artificial intelligence and petri net modelling

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Abstract

Nowadays energy crisis is considered an essential active issue for future urbanization in megacities. While the rate of population growth increases, the volume of municipal solid waste production increases significantly. This highlights the need of Sustainable Development Goals (SDGs) for both developed and developing countries. This paper introduces a novel smart framework for supplying biogas energy to study waste management and energy supply in green buildings. This framework integrates the Response Surface Methodology (RSM), Artificial Intelligence (AI), and Petri net modeling. Firstly, the particular biogas generation setup is invented for food waste digestion by integrating Sequencing Batch Reactors (SBR) sludge and Clostridial microorganisms. Before experimental practices, for evaluation of waste characterizations, the quartering and coning method is utilized. In the experimental practices, different variables including Sludge/Waste, Inoculum (Clostridiales/Waste), pH, Temperature and, time, are appraised in the lab-scale setup. Also, in the experimental section for measuring the variables through biogas production procedure, three protocols containing EPA-821-R-01-015, Organic Matter and alkalinity evaluation by American Public Health Association (APHA, 2017) and Einhorn Saccharometer technique are utilized. The optimum conditions are appraised based on Central Composition Design (CCD) using RSM. Artificial intelligence techniques including the Random Tree (RT), Random Forest (RF), Artificial Neural Network (ANN) and, Adaptive-

Network-based Fuzzy Inference System (ANFIS) are employed. Plus, for creating the optimum condition, a dynamic controlling system Petri Net modeling is used.

The outcomes of present investigation have illustrated that the optimum conditions for Sludge/food Waste (S/W), *Clostridiales*/ food Waste (C/W), pH, Temperature (T) and Retention time (t) as effective parameters are equal to 163 mg/g, 54 mg/g, 7, 30 °C and 55 days, respectively. Likewise, the analysis of variance (ANOVA) assessment demonstrated that the most effective parameters are S/W and T with high amount of F-value and low amount of P-value. Plus, between all machine learning methods, ANFIS with 0.99 correlation coefficient had the best accuracy for Accumulated Biogas Production (ABP) based on effective factors.

Sludge and Clostridial based bio-engine are compared with together asper biogas/methane generation and fluctuation of Total Organic Carbon (TOC), Chemical Oxygen Demand (COD) and total alkaline are appraised. The outcomes have demonstrated that efficiency of sludge-based system is two times more than Clostridial based reactors, because of available nutrient and active microorganisms. Finally, Circular Economy (CE) scrutinizing have proved that with application of this method in a green building, all electrical energy/heat demands can be supplied by 381 kwh (3051 MJ) in the case study (In one residential unit). Also, the remained digested food waste with 310 mg/L COD is valuable for gardening activities in green buildings.

Finally, with the outcomes of present study, some different scientific issues such as clean energy supplying in green buildings, smart sustainable biogas production control system, Integrated Solid Waste Management (ISWM), CE and SDGs in green buildings are tackled as a novel framework in smart and sustainable cities.

Keywords: *Biogas, Food Waste, Sludge, Clostridial Microorganisms, Response Surface Methodology, Artificial Intelligence, Petri Net Modelling;*

1. Introduction

One of the main concerns in Green Building Concepts (GBC) [1], Sustainable Development Goals (SDGs) [2] and Clean Technologies Theory (CTT) [3] is related to stable energy supplying in short, middle and long terms [4]. When energy demand is increased in different megacities of developing countries based on population accumulation [5], consumerism [6], cultural diversion [7] and global warming effects [8] which is continued every year. Plus, waste generation, especially biological wastes in developing countries, is augmented as per life style changing [9] and developing urbanization in some countries such as Iran [10], India [11] and China [12]. Energy crisis and biological waste generation problem are noteworthy challenges when they are seen separately, but, in a holistic view of GBC, they can be considered as an opportunity for biogas production for implementation of CTT in future lifestyle of developing countries [13].

Biogas generation from biological wastes is assumed as a green method for Integrated Solid Waste Management (ISWM) during anaerobic digestion in household reactors [14, 15]. The scheme of

Circular Economy (CE) in biogas generation from biological waste and biochemical reaction are illustrated in Figs. 1 [16-18] and 2 [19-21], respectively. According to Fig. 1, with CE approach the threats of waste generation can be converted to opportunities for energy demand crisis and fertilizer providing in green building's plants from digested wastes [22]. Whereas, as per Fig. 2, it is clear that biogas generation is done in four stages containing hydrolysis, acidogenesis, acetogenesis, and methanogenesis [23].

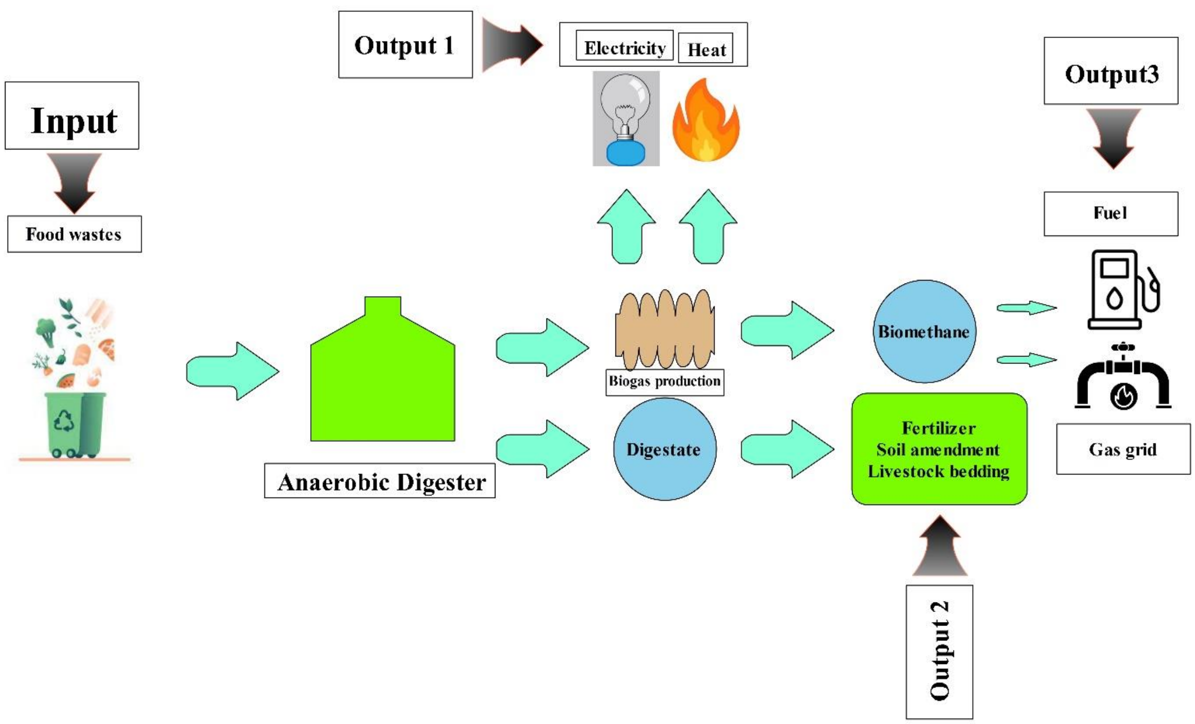

Fig. 1. The schematic plan of biogas generation cycle [16-18].

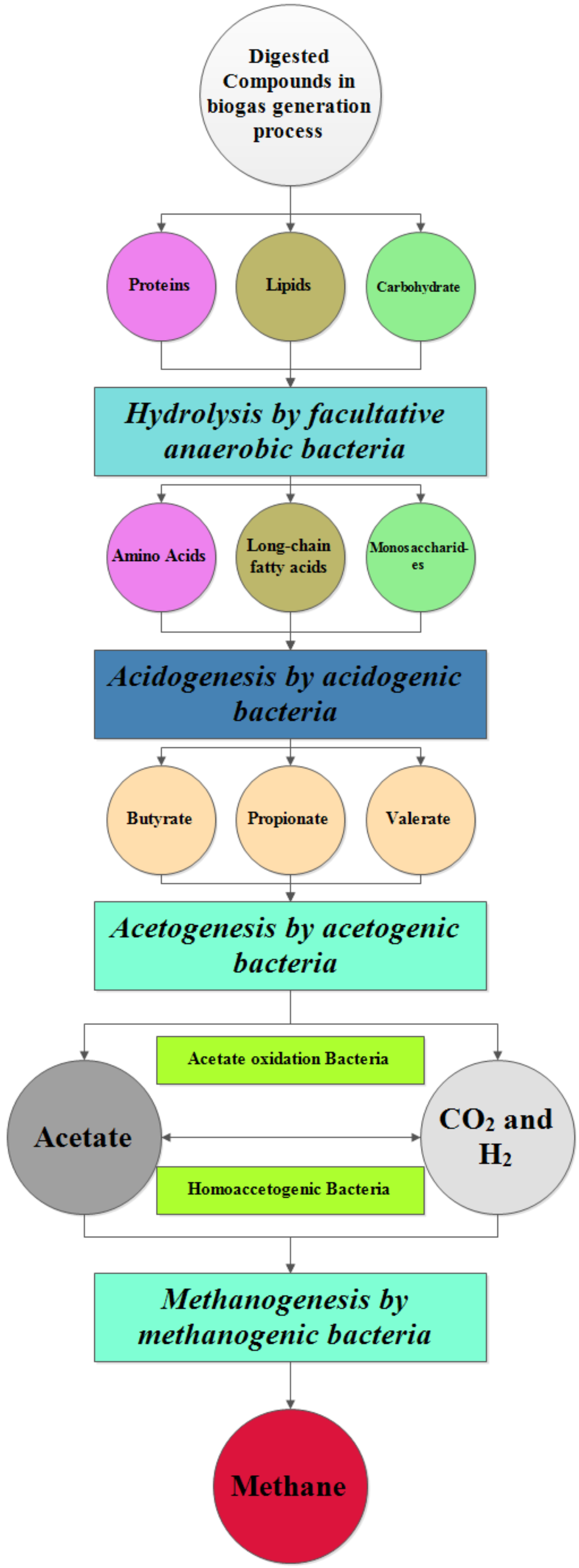

Fig. 2. The schematic plan of biochemical reactions [19-21].

Cavaignac et al. (2021) have presented a novel concept for operation of biogas reactors with considering technical, economic and environmental aspects. In the mentioned study, main issue was related to amine scrubbing role in biogas generation enhancing. Plus, by application of Life Cycle Assessment (LCA) method, emission of CO_2 was predicted with high accuracy [24]. Also, Miranda et al. (2021) have evaluated green technologies for energy supplying in some countries including Brazil, Russia, India, China, and South Africa (BRICS). For the mentioned goal, Methodi Ordinatio methodology with concentration on sustainability indices was used [25]. Plus, Niu et al. (2021) have designed a biogas system for rural usages energy providing in China. In this study, environmental and social benefits have been scrutinized by monetization method. Likewise, the performance of partially competitive strategy is discussed for medium- and large-scale biogas projects (MLBPs) [26]. Abanades et al. (2021) have presented a framework for biogas generation in the globe based on critical review concept [27]. Lomazov et al. (2021) have optimized biogas energy production plants with application of fuzzy and genetic algorithm techniques [28]. Stürmer et al. (2021) have compared the biogas production based on agricultural wastes in different regions. The declared research has assessed legal framework and regional structures on biogas production [29]. Jung et al. (2021) and Akbulut et al. (2021) have designed local biogas system in large-scale with considering syngas system energy supplying and energy planning in Malatya, respectively [30, 31]. Brémond et al. (2021) have presented a novel framework for improvements of solid digestion process in Continuously Stirred Tank Reactors (CSTRs) with agricultural waste feeding. In the declared study, some different strategies are assessed for enhancing the efficiency of biogas production [32]. Naquash et al. (2021) have presented some outcomes for production of Liquefied Natural Gas through solidification of CO_2 through biogas procedure. Likewise, in the mentioned investigation, all simulations are done in Aspen Hysys® v11 platform [33]. Moreover, Zhang et al. (2021) have designed food-waste-to-energy system as decentralized energy supplying approach. The researchers have concentrated on organic matter loading and temperature effects on biogas production efficiency. Also, with application of Sankey diagram in energy flow, the performance of anaerobic digestion and Combined Heat and Power (CHP) are scrutinized [34]. Wu et al. (2021) have scheduled the biogas-solar-wind as Integrated Energy Systems (IESs) in a case study. In the mentioned study, for programming energy usages multi-objective optimization (MOO) are utilized [35]. Su et al. (2021) have presented a novel system for thermal collecting of bio-methane production with application of photovoltaic facilities. In the avowed research, reducing the fossil fuel consumption are proposed as cost function [36].

As the reviewed investigations, application of Artificial Intelligence (AI) and Response Surface Methodology (RSM) for biogas generation in green building energy supplying is so rare as a research gap and this research wants to present a novel smart model for bio-energy contributing.

The present study aims to:

- Inventing biogas setup for household energy applications based on biological wastes in green buildings with combination of *Clostridiales*, wastewater treatment plant's sludge and food wastes digesting activities.
- Optimizing the effective parameters on biogas production in green buildings by Central Composition Design (CCD)-RSM technique.
- Creating smart controlling model for operating system by Random Tree (RT), Random Forest (RF), Artificial Neural Network (ANN) and Adaptive-Network-based Fuzzy Inference System (ANFIS) soft computations.
- Presenting controlling model in green buildings as per Petri net system.

In the present study, with application of CCD-RSM technique, the optimum conditions are determined and likewise, the number of experimental runs are reduced. On the other words, by CCD-RSM method plus enhancing the performance of biogas production process, the experimental costs are decreased. In the followings, the AI computations evaluate the behavior of bio-system performance for controlling possible reactor's problems in the especial situations with prediction the future manners. Finally, with comparison of the outcomes of AI and CCD-RSM, the effective method for controlling and prediction of biogas production are suggested as the scientific fact.

The rest of this paper is organized as follows: Section 2 provides the materials and methods including the framework of this research, used materials, instrumentation, lab-scale setup, microbiological methods, optimization, prediction and controlling models. Section 3 presents the test results and provides the discussion on the results. Finally, a summary of this research with findings and recommendations, is concluded in Section 4.

2. Materials and methods

2.1. Case study

The present research is done in a residential complex with fifteen household units which is illustrated as per Fig. 3. Also, monthly electrical demand (Fig. 4) of each unit is demonstrated in Fig. 4 according to PVSystem simulations software [37]. Plus, approximate analysis of food wastes which is appraised based on quartering and coning method [38] is summarized in Table 1.

Fig. 3. Location of Mashhad, Iran.

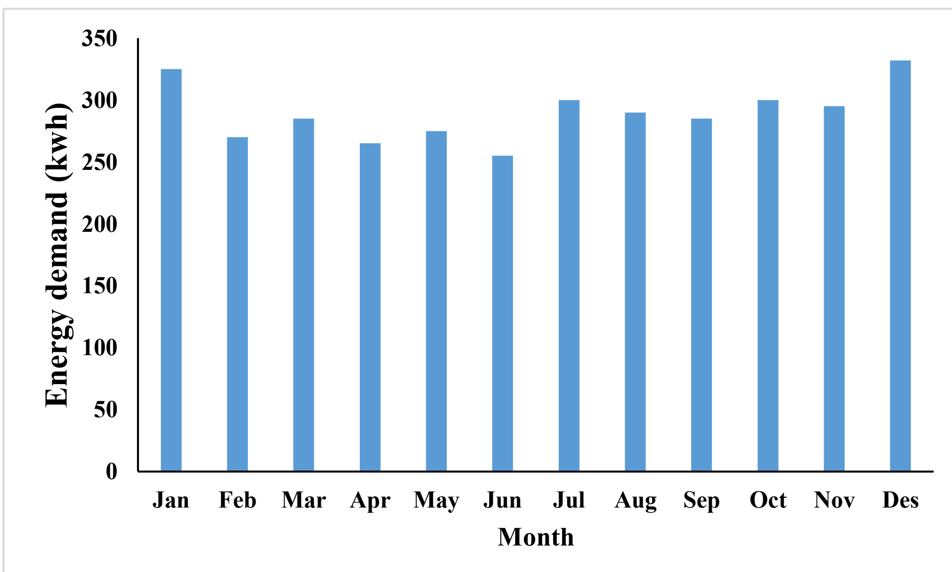

Fig. 4. The pattern of electrical energy consumption in the case study in Mashhad, Iran.

Table 1. Approximate specification of residential wastes as per quartering and coning method in present research.

Waste type	Percentage	Moisture (%)
Paper	21	8
Glass	9	2
Food waste	40	82
Plastic waste	27	12
Cloth waste	3	15

2.2.Research roadmap

In this study, research roadmap is divided to four sections such as experimental efforts, optimization and statistical evaluations, predictive models and controlling algorithm as a Decision Support System (DSS) which are demonstrated in Fig. 5.

According to Fig. 5, in the first step, the energy demands of the case study is computed by simulation and application of some different data banks. By applying this section, the value of energy demand is determined in different months. Then, with quartering and coning method, the quality and quantity of available solid wastes are measured as the first section of second stage. Plus, in the second section the lab scale setup is designed and built and then in the last section of this stage, the experimental efforts are started. For design of experiments, CCD-RSM method is employed as sensitive analysis, optimization and regression prediction equations. After, optimizing the mentioned experiments by CCD-RSM, the suggested optimum conditions are compared by real test's amounts until reaching to desirable precision. If the CCD-RSM values are not fit to real experiments, the CCD-RSM should be redesigned. In the next stage, by the CCD-RSM outcomes, Petri Net modelling are done for creating the concept of smart operation system of biogas generation process with focusing on approved optimum conditions. In the fifth stage of present research, the RF, RT, ANN and ANFIS computations are utilized for smart forecasting microorganism's behavior through the biogas production procedure. Finally, after assessment of biogas energy supplying performance in this study, a conceptual model is designed for implementation of SDGs. CE and ISWM in the research.

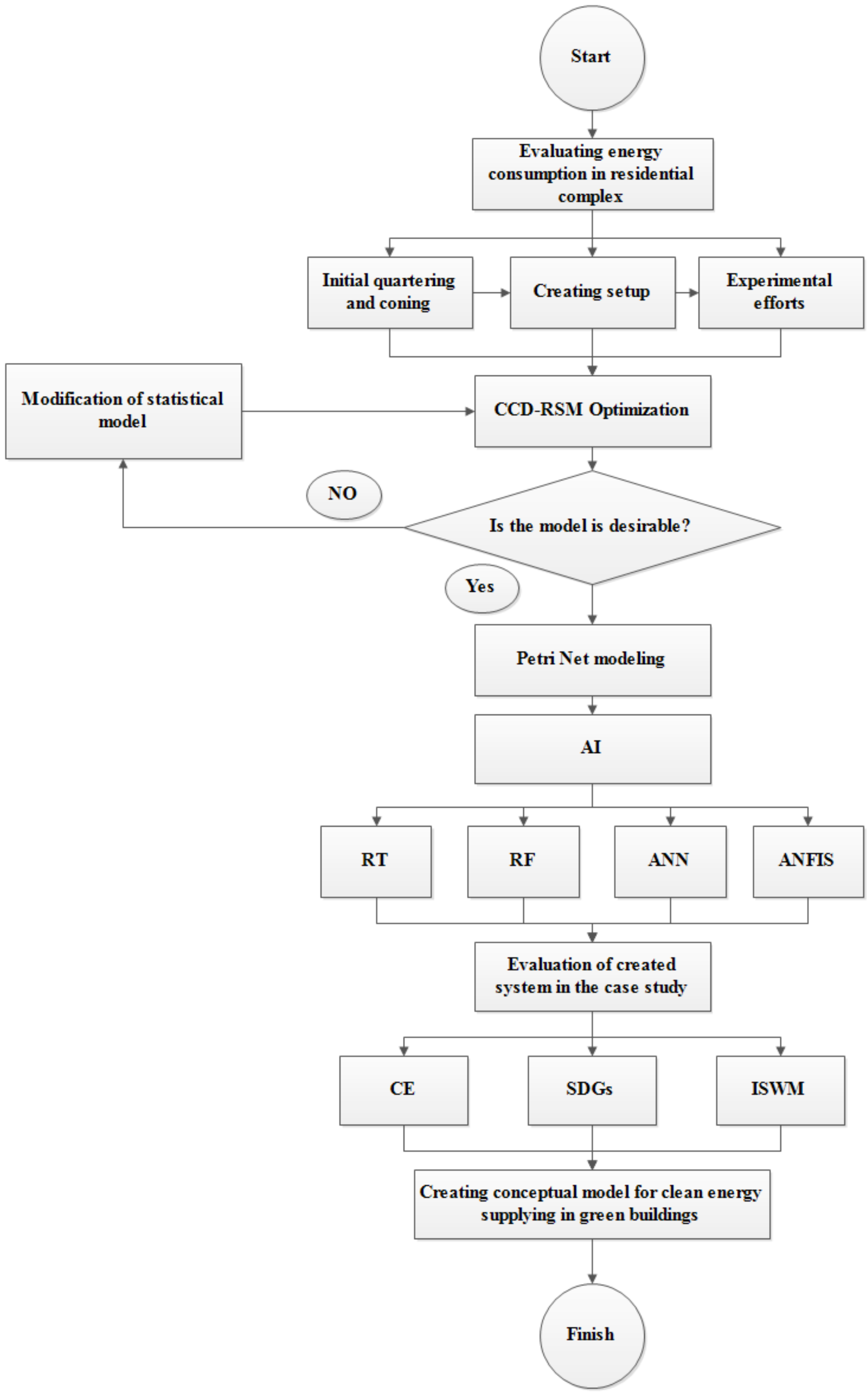

Fig. 5. The research roadmap of present study (CCD-RSM: Central Composition Design-Response Surface Methodology, AI: Artificial Intelligence, RT: Random Tree, RF: Random Forest, ANN: Artificial Neural Network

and ANFIS: Adaptive-Network-based Fuzzy Inference System, CE: Circular Economy, SDGs: Sustainable Development Goals and ISWM: Integrated Solid Waste Management)

2.3.Materials and instrumentation

All reagents and materials for experimental practices and sampling are shown in Table 2. Likewise, sampling is done three times with quartering and coning method, initial and final gas generation tests. Whereas, all applied instruments are utilized for sampling, gas measurement and effective parameters determinations are mentioned in Table 3.

Table 2. Crucial materials and regents for present study.

Compounds	Conditions	Company
NaOH	Molecular weight is equal to 40 gr mol^{-1}	Sigma Aldrich, USA
Secondary sludge sedimentation as an inoculum	This sludge have been provided from secondary clarifier tank in Sequencing Batch Reactor (SBR)	From Al-Teymour wastewater treatment plant in Mashhad City
Silicone glue	Silicon, nanopowder, <100 nm particle size (TEM), ≥98% trace metals basis with 28.09 gr mol^{-1} molecular weight	Sigma Aldrich, USA
N_2 gas	Nitrogen, ≥ 99.998% with 28.01 gr mol^{-1} molecular weight	Sigma Aldrich, USA

HNO_3	70% purity and with 63.01 gr mol^{-1} molecular weight	Sigma Aldrich, USA
Mixed food waste	It is obtained after one day	From Case study in Mashhad City
Clostridiales	Liquid sample	Iranian Genetic Bank (IGB)

Table 3. Functional equipment in present study.

Instrument	**Conditions/model/description**	**Company**
Vacuum flask	With glass hose connector	VWR® International Co.
Vacuum pump	Suction Capacity 550 to 15000 m^3 h^{-1}	PPI pumps Co.
Lab scale storage	Borosilicate Glass	BOROSIL Technologies Co.
One-liter glass batch-mode digester	High pressure and temperature mode	Nunc Lab-Tek Co.
pH meter	Thin. Professional.	Hanna pH meter Co.
Total Organic Carbon meter	multi EA® 5100 for Micro-Elemental Analysis	Analytik Jena Co.
Autoclave	Vertical floor-standing autoclaves (top-loading) from 40 to 150 liters chamber volume	Systec. V-Series Co.
Bain-marie	Stainless Steel Bain Marie (Brand:SSFW), 220V	Mindiamart Co.

Oven	Drying oven 125 basic dry (5 - 250 centigrade degree)	IKA Co.
Electrical control circuit	Micro Pragma	Schneider Electric Co.
Chemical Oxygen Demand meter	Fits 16mm or 13mm Hach COD vials, Test N Tube vials or TNTplus™ vials	Hach Co.
Submersible pump	SKU: ECO-185	Lab society Co.
Temperature sensor	Sensor Net Connect Temperature Monitoring	Plug & Track Co.
Pneumatic connections	UNIFLEX™ BASIC model	BROEN–LAB Co.
Electro thermal elements	Steel with 403 grade and temperature threshold is equal to 400 °C	Iran element Co.
Gas storage bag	High pressure and temperature mode	Nunc Lab-Tek Co.
Heat water tank	High pressure and temperature mode	Nunc Lab-Tek Co.
Einhorn's saccharometer	The carbon dioxide created in the fermenting process would rise to the top of the closed tube and force the level of liquid down.	VWR Co.
20 cc syringe	Standard plastic mode	Samen Co.

2.4.Lab-scale setup and experimental methodology

The schematic plan of biogas lab scale setup including mechanical devices, chemical sensors and equipment and structural tools are depicted in Fig. 6. Also, the algorithm of experimental methods in each run is illustrated in Fig. 7.

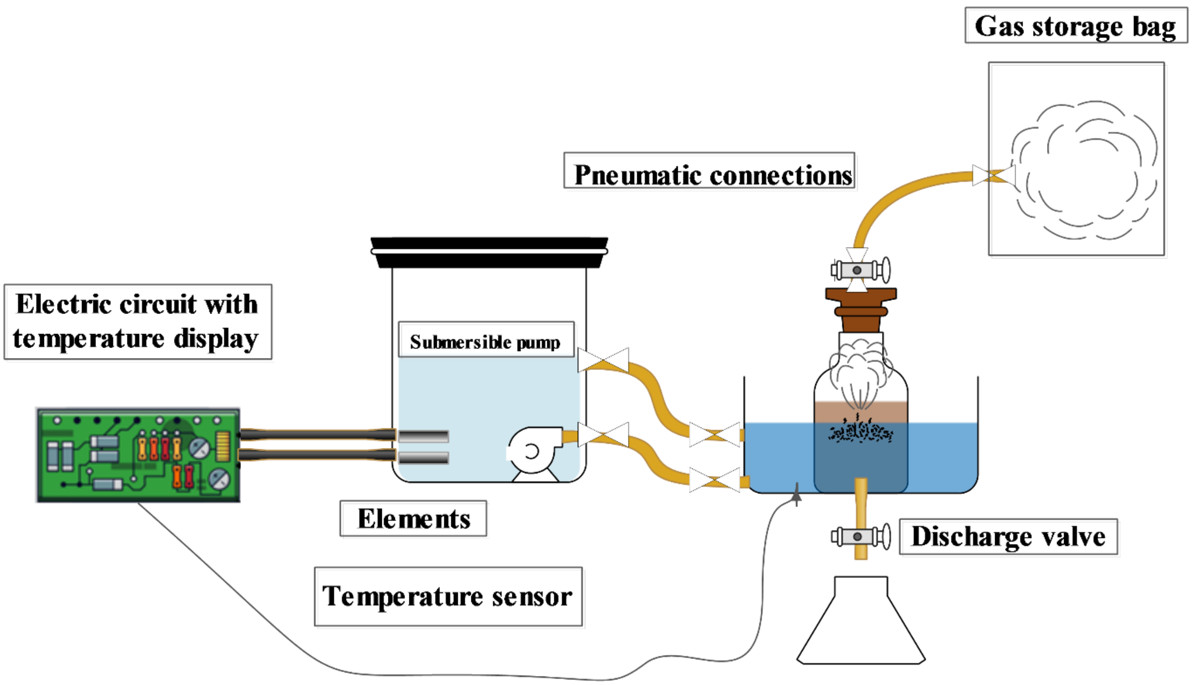

Fig. 6. Schematic plan of bio-energy reactor in present study.

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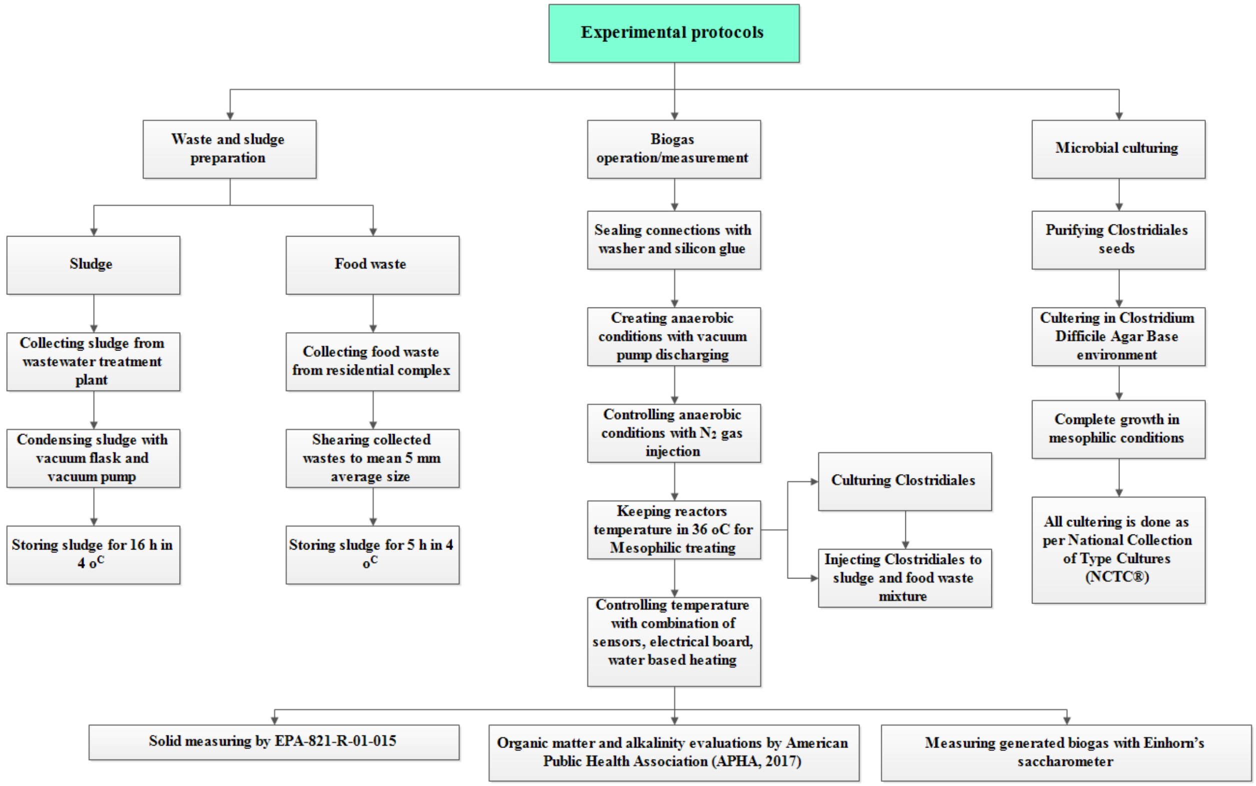


Fig. 7. The algorithm of experimental methods in present study [39-41].

2.5.CCD-RSM model

In this study, CCD-RSM statistical model is used in Design Expert 7.0.0 software which it determines sensitive analysis, optimum conditions and mathematical regression based predictive model for energy supplying in green buildings. Also, in the Design of Experiments (DOE), value of alpha is set in 1.2 amount [42]. The specifications of DOE for each effective parameter in this study is demonstrated in Table 4. In this research Accumulated Biogas (methane) Production (ABP) is assumed as a cost function (response) in ml unit. Both sludge and Inoculum play role as bio-engine for degradation of food waste in biogas generation cycle. But, in present investigation, the character of each one is separated for comparison of wastewater treatment plant's bacteria and *Clostridiales* gas generation abilities. The key parameters for experimentation are selected as per literature review evaluations in different investigations [29-31, 39-41].

Table 4. The variables and values used for biogas process optimization in CCD.

Variables	**Unit**	**Symbol**	**Coded factors level**				
			-1.2 (Low)	**+1**	**0**	**-1**	**1.2 (High)**
Sludge/Waste	mg/gr	S/W	90	100	150	200	210
Inoculum (Clostridiales/Waste)	mg/gr	C/W	6	10	30	50	54
pH	____	pH	5.2	6	7	8	8.2
Temperature	°C	T	6.5	25	35	45	48.5
Time	day	t	6	10	30	50	54

After determination of optimum conditions, for creating smart controlling models Petri Net [43] concept is utilized. In the declared model, each adjustable factor and conditional values are put in place and transition functions, correspondingly. The algorithm of Petri Net modelling design is shown in Fig. 8.

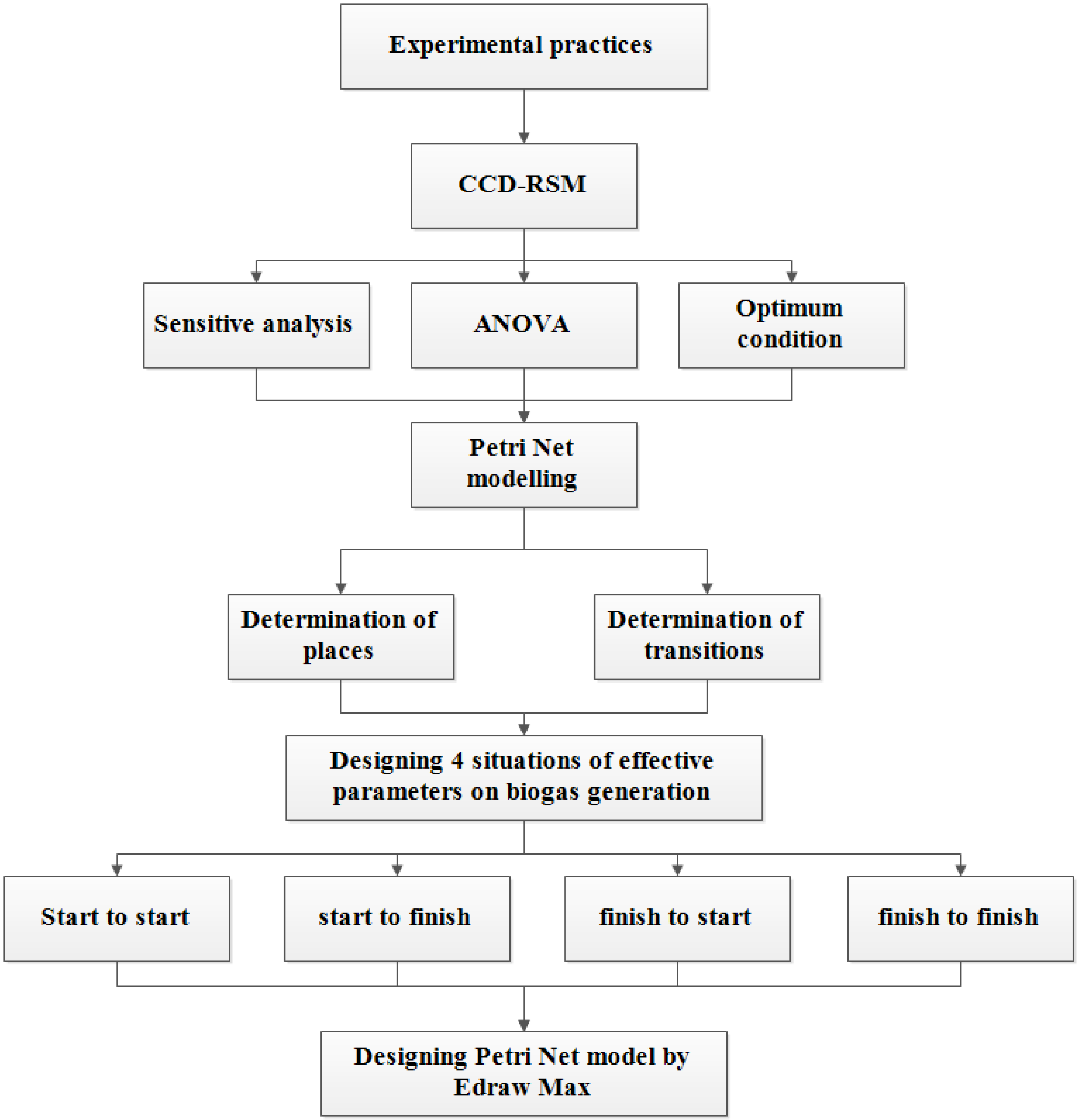


Fig. 8. Schematic plan of Petri Net modelling in present study.

2.6.AI techniques

In the present study, for creating the predictive model as smart controlling systems, some different machine learning computations such as ANN [44], ANFIS [45], RT [46] and RF [47] are used. For implementation of the mentioned algorithm MATLAB 2013 b and WEKA software are performed which is described in Table 5.

Table 5. The AI computation specifications in present research.

Method	Software	Conditions
ANN	WEKA 3.9	Multilayer perceptron and percentage split is set on 90%
RT	WEKA 3.9	Cross-validation folds are set on 30
RF	WEKA 3.9 and MATLAB 2018b®	Percentage split is set on 80%
ANFIS	MATLAB 2018b®	Sugeno, membership functions are three Gaussian type 2, optim method and number of epochs are selected equal to hybrid and 70, correspondingly.

3. Results and discussions

3.1. Optimization and experiments

The outcomes of experimental efforts as per analysis based on CCD-RSM technique are summarized in Table S.1. Plus, the fitness of Linear, 2FI, Quadratic and Cubic distributions have illustrated that the R-Squared and Predicted R-Squared of quadratic function is more acceptable in comparison of other ones (Table 6). According to Table 6, quadratic model with 0.92 and 0.64 R-Squared and Predicted R-Squared can achieve the best outcomes in curve fitting aspect (Equation 1). In mathematical viewpoint, quadratic model could satisfy ABP (ml) according to effective parameters containing S/W, C/W, pH, T and t. But, for prediction ABP, the created statistical model with 0.62 Predicted R-Squared cannot meet forecasting expectations. Thus, for estimations of ABP, application of AI can be useful as an online soft monitoring system in detail of DSS.

Table 6. The results of mathematical models in CCD-RSM.

Source	Std. Dev.	R-Squared	Adjusted R-Squared	Predicted R-Squared	PRESS	
Linear	1518.185	0.20	0.119179	0.0187	1.26E+08	
2FI	1647.652	0.28	-0.03745	0.18523	1.96E+08	
Quadratic	1125.946	0.92	0.515523	0.64	1.26E+08	Suggested
Cubic	867.7422	0.91	0.712247	-0.79628	2.3E+08	Aliased

Equation 1

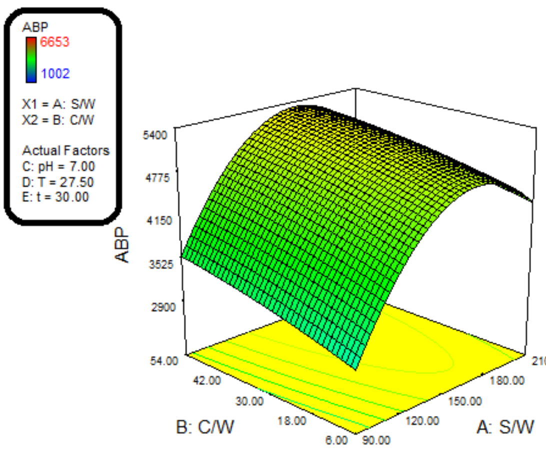
$$ABP = -46061.41463+126.90239 * S/W+85.91509 * C/W+9832.81639 * pH+237.44436 * T-4.22495 * t-0.034750 * S/W * C/W-3.26625 * S/W * pH+0.026214 * S/W * T-0.10325 * S/W * t-12.65625 * C/W * pH-0.23429 * C/W * T+1.04234 * C/W * t-0.81786 * pH * T-1.35625 * pH * t+0.035000 * T * t-0.29929 * (S/W)^2-0.10317 * (C/W)^2-612.44931 * (pH)^2-3.62682 * (T)^2+0.12339 * (t)^2$$

The outputs of analysis of variance (ANOVA) evaluations and sensitive analysis is demonstrated in Table 7 and Fig. 9, respectively. With considering to Table 7, The P-value of model and its lack of fit are computed equal to less than 0.0001 (significant) and 0.1415 (not significant) respectively, which it conveys high level of validity in achieved statistical model. Also, according to Table 7, the P-Value of both S/W and T factors are less than 0.0001. Therefore, S/W and T have the most significant effect on ABP in comparison other ones. Likewise, the F-value of S/W with 89.73 amount is more than T parameter (with 11.09) and it determines that S/W is the most important parameter between all effective factors on ABP. Whereas, the least significant parameter is related to t with 0.28 and 1.19 P-value and F-value correspondingly. The sensitive analysis of dual effective parameters vs ABP is illustrated in Fig. 9. As per this Fig., the most slope variations are related to S/W and T factors which illustrate the influences of them on ABP in comparison of other ones.

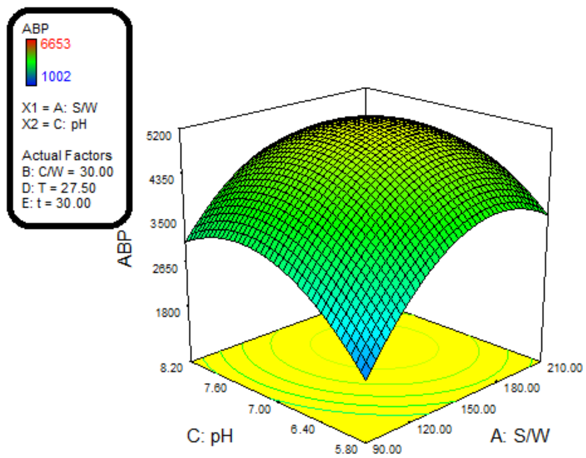
Table 7. The results of ANOVA evaluation in CCD-RSM.

Source	Sum of Squares	df	Mean Square	F Value	p-value (Prob > F)	
Model	91455700	20	4572785	3.60	< 0.0001	significant
A-S/W	10235044	1	10235044	89.73	< 0.0001	
B-C/W	1611124	1	1611124	1.27	0.26	
C-pH	3700598	1	3700598	2.91	0.09	
D-T	9741058	1	9741058	11.09	< 0.0001	
E-t	1517780	1	1517780	1.19	0.28	
AB	38642	1	38642	0.03	0.86	
AC	853471.1	1	853471.1	0.67	0.41	
AD	16836.13	1	16836.13	0.01	0.90	
AE	341138	1	341138	0.27	0.60	
BC	2050313	1	2050313	1.61	0.21	
BD	215168	1	215168	0.17	0.68	
BE	5562780	1	5562780	4.38	0.04	
CD	6555.125	1	6555.125	0.005	0.94	

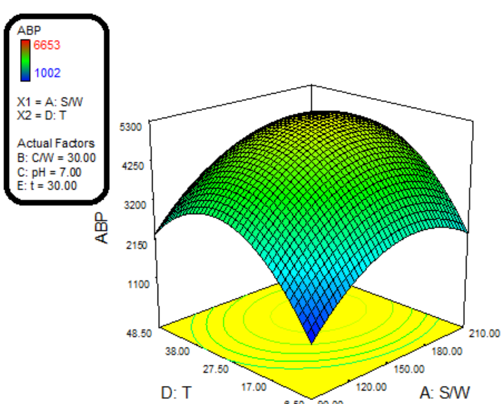
CE	23544.5	1	23544.5	0.018	0.89	
DE	4802	1	4802	0.003	0.95	
A^2	2832988	1	2832988	2.23	0.14	
B^2	8618.599	1	8618.599	0.006	0.93	
C^2	1898166	1	1898166	1.49	0.23	
D^2	6243064	1	6243064	4.92	0.03	
E^2	12327.59	1	12327.59	0.009	0.92	
Residual	36764876	29	1267754			
Lack of Fit	32146334	22	1461197	2.21	0.14	not significant
Pure Error	4618542	7	659791.6			
Cor Total	1.28E+08	49				



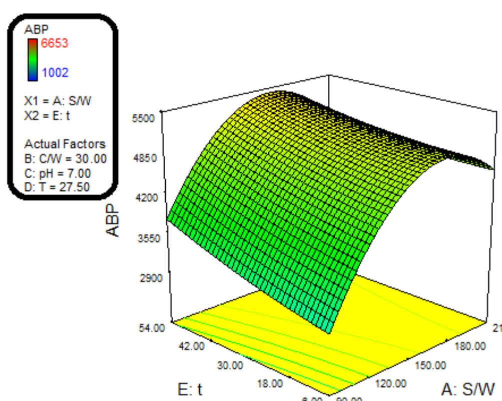
(a)



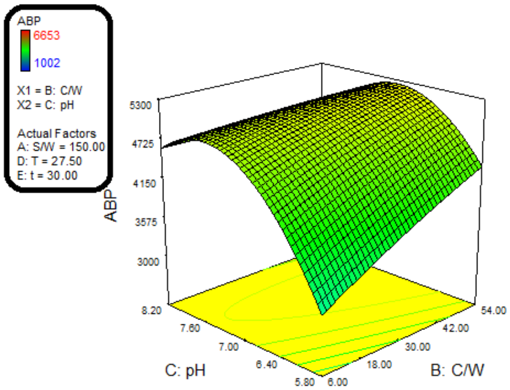
(b)

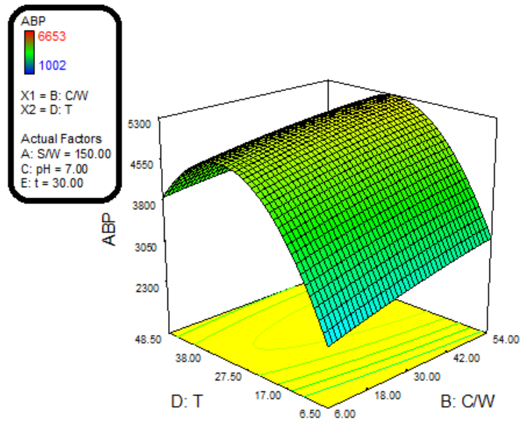


(c)



(d)


ABP
6653
1002
X1 = B: C/W
X2 = C: pH
Actual Factors
A: S/W = 150.00
D: T = 27.50
E: t = 30.00
ABP
5300
4725
4150
3575
3000
C: pH
8.20
7.60
7.00
6.40
5.80
B: C/W
6.00
18.00
30.00
42.00
54.00


ABP
6653
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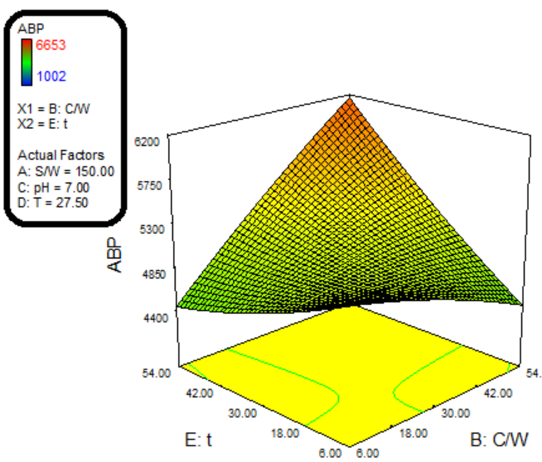
X1 = B: C/W
X2 = D: T
Actual Factors
A: S/W = 150.00
C: pH = 7.00
E: t = 30.00
ABP
5300
4550
3800
3050
2300
D: T
48.50
38.00
27.50
17.00
6.50
B: C/W
6.00
18.00
30.00
42.00
54.00

(e)

(f)


ABP
6653
1002
X1 = B: C/W
X2 = E: t
Actual Factors
A: S/W = 150.00
C: pH = 7.00
D: T = 27.50
ABP
6200
5750
5300
4850
4400
E: t
54.00
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B: C/W
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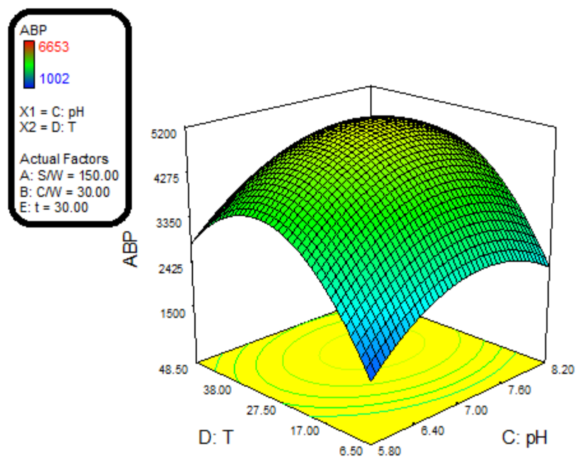
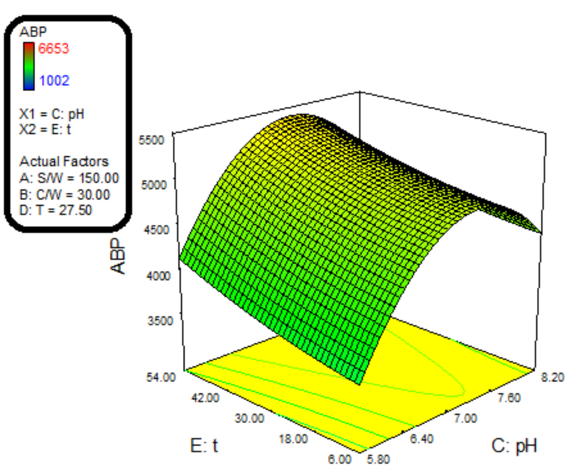
42.00
54.00


ABP
6653
1002
X1 = C: pH
X2 = D: T
Actual Factors
A: S/W = 150.00
B: C/W = 30.00
E: t = 30.00
ABP
5200
4275
3350
2425
1500
D: T
48.50
38.00
27.50
17.00
6.50
C: pH
5.80
6.40
7.00
7.60
8.20

(g)

(h)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X2 = E: t
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ABP
5500
5000
4500
4000
3500
E: t
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C: pH
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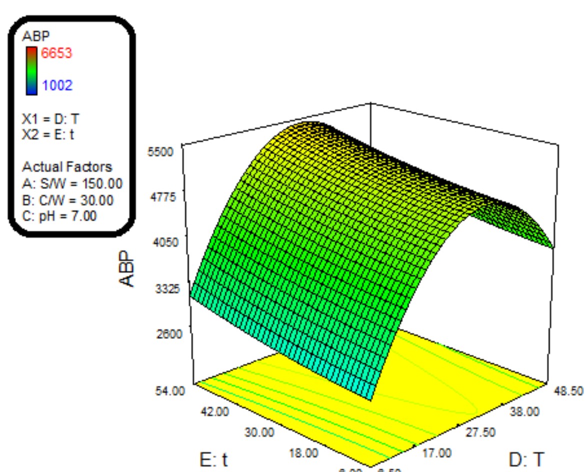
7.00
7.60
8.20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ABP
5500
4775
4050
3325
2600
E: t
54.00
42.00
30.00
18.00
6.00
D: T
6.50
17.00
27.50
38.00
48.50

(I) **(J)**

Fig. 9. The sensitive analysis of effective parameters in CCD-RSM.

The normal plot of residuals is demonstrated in Fig. S.1 which shows distribution of ABP's results in neighborhood of normal diagram. So, the results of experimental activities follow normal statistical distributions in different runs. The five suggested optimum conditions based on CCD-RSM computations are summarized in Table 8. According to declared Table, optimum values of S/W, C/W, pH, T and t are equal to 163 mg/g, 54 mg/g, 7, 30 °C and 55 days, respectively. Also, the mentioned suggestions are examined in lab scale setup with three repetitions and 6310.2 ml, 6282.3 ml and 6325.1 are measured as experimental outputs. While, the mean value of predicted ABP with 6259.96 ml has 99.6% accuracy with mean value of experimental results (with 6306.1 ml). Desirability of mathematical prediction outcomes vs variations of S/W and C/W is illustrated in Fig. S.2.

Table 8. The outcomes of optimum conditions in CCD-RSM.

Number	S/W	C/W	pH	T	t	Predicted ABP (ml)	Experimental outcomes repetition 1- ABP (ml)	Experimental outcomes repetition 2- ABP (ml)	Experimental outcomes repetition 3- ABP (ml)
1	163.1	54	6.97	31.02	55	6261.1			
2	163.69	54	6.98	30.88	52	6260.3			
3	161.76	54	6.99	31	54	6260.2	6310.2	6282.6	6325.5
4	161.45	54	6.93	30.73	51	6259.8			
5	163.08	54	6.92	30.33	53	6258.4			

3.2.Smart control systems

In the followings, experimental outcomes modeled by ANN, RF and RT machine learning algorithms which is shown in Table 9. As per the mentioned soft computing systems, the most accuracy with 0.93 correlation coefficient is related to RT algorithm. Plus, ANN and RF algorithms are in the next places with 0.91 and 0.87 correlation coefficients, respectively. Also, plot matrix of input and output data is demonstrated in Fig. S.3. The computational RT algorithm and RT conceptual model are demonstrated in Equation S.1 and Fig. 10, respectively. With following this tree, ABP of each fabulous condition can be predicted as a soft sensor.

Table 9. The statistical outcomes of ANN, RF and RT algorithms in present research.

Statistical parameters	ANN	RF	RT
Correlation coefficient	0.91	0.87	0.93

Mean absolute error	890.97	1070.74	755.6
Root mean squared error	952.41	1207.11	870.98
Relative absolute error	51.58%	58.21%	43.74%
Root relative squared error	49.94%	61.23%	45.67%
Total number of instances	5	10	5

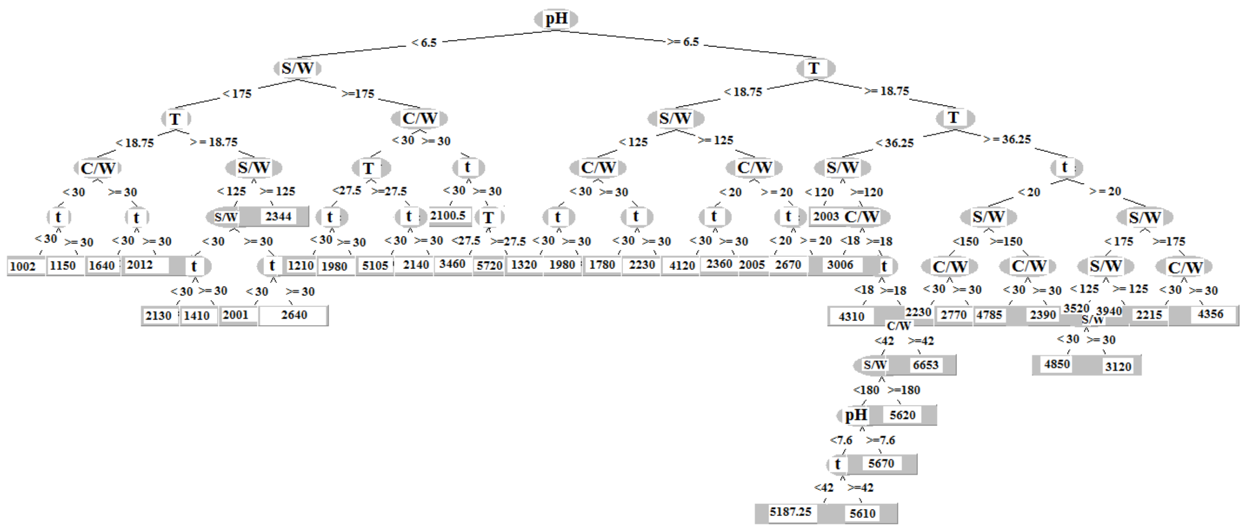


Fig. 10. The RT conceptual model in present study.

The confusion matrix and parallel coordinates plot of RF algorithm are illustrated in Fig. 11 and S.4, correspondingly. According to Fig. 11, the population of positive predictive value is more than negative predictive value which demonstrates validity of RF computations in this research. Also, the parallel coordinates plot depicts the high level of correct predictions for ABP values as per effective parameters. With focusing on Fig. S.4, staccato lines (as an incorrect prediction) cannot be seen in comparison of allied lines (as a correct estimation).

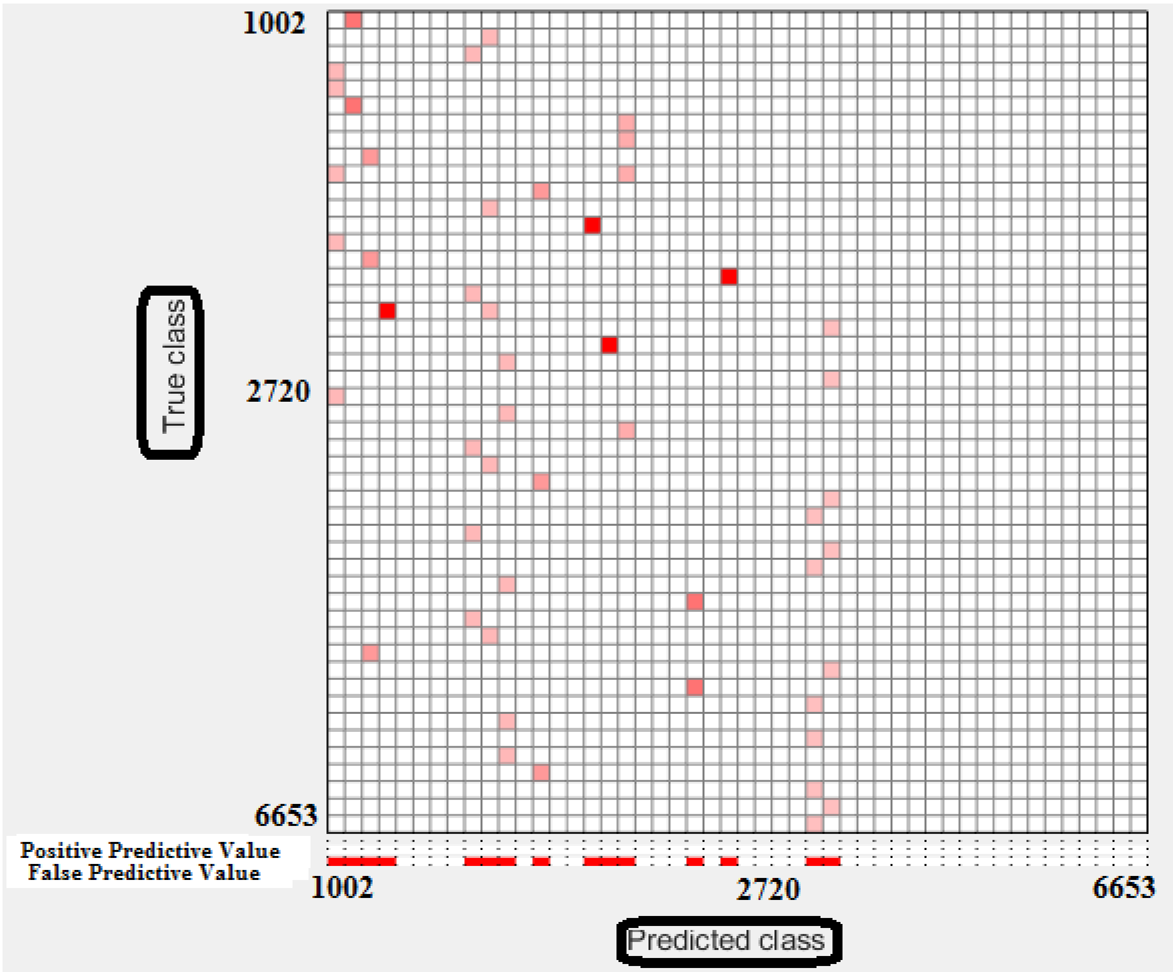


Fig. 11. The confusion matrix of RF algorithm in present study.

Structural of ANFIS model for smart estimation of ABP as per S/W, C/W, pH, T and t with 3 membership functions is depicted in Fig. 12. Also, adaption of training data and FIS outputs is declared in Figs. S.5-6 and Table 10 which accent to high level of accuracy in ANFIS computations. Likewise, duo to evaluation of significant degree in each effective parameter for ABP the dual sensitive analysis of ANFIS calculation algorithm is demonstrated in Fig. 13. With regard to Fig.13, it is clear that S/W and T parameters have the most slope variations on the 3D plots and this indicates the high degree of importance of these factors in comparison of other parameters.

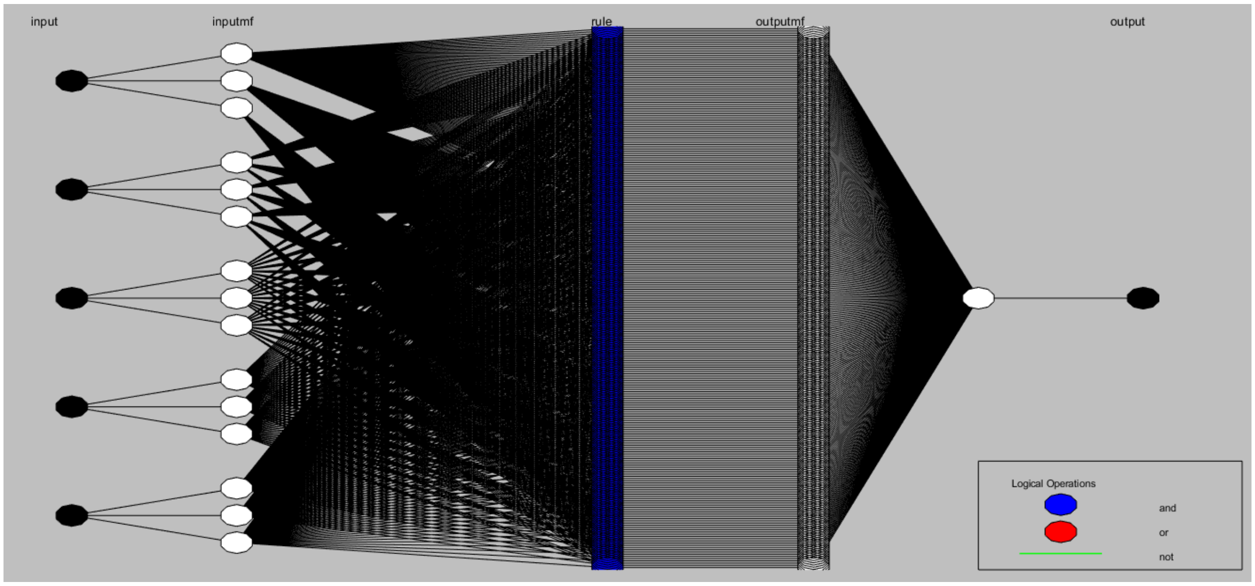
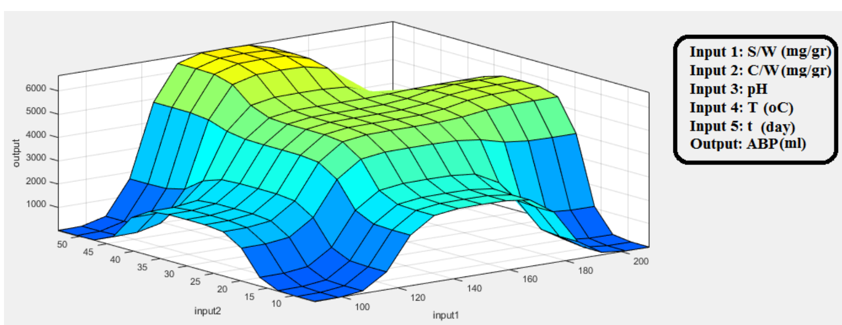


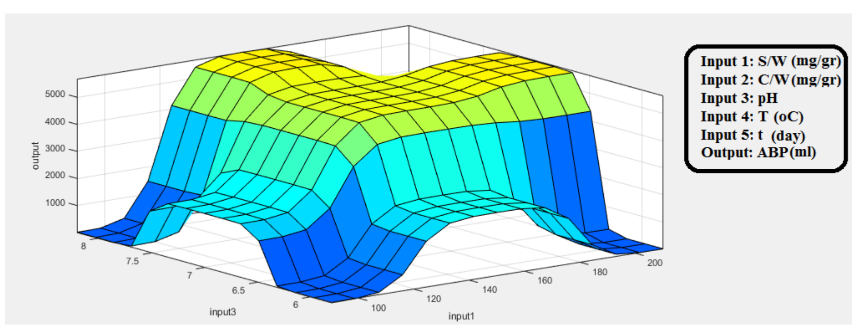
Fig. 12. Structural ANFIS computational algorithm in present study.

Table 10. The statistical outcomes of ANFIS algorithm in present research.

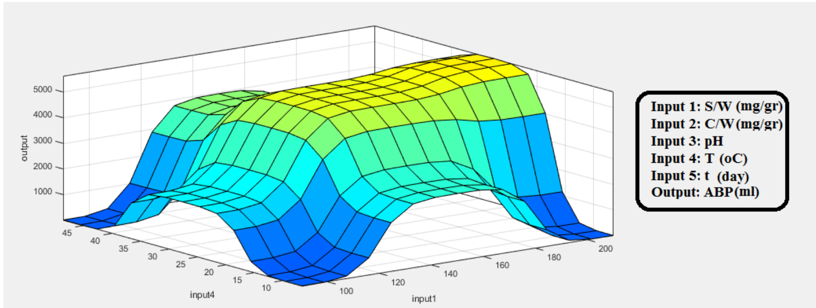
Regression Statistics	
Multiple R	0.981825
R Square	0.96398
Adjusted R Square	0.963229
Standard Error	310.1929
Observations	50



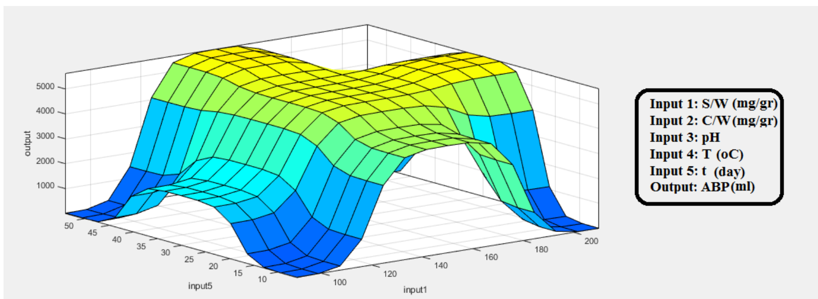
(a)



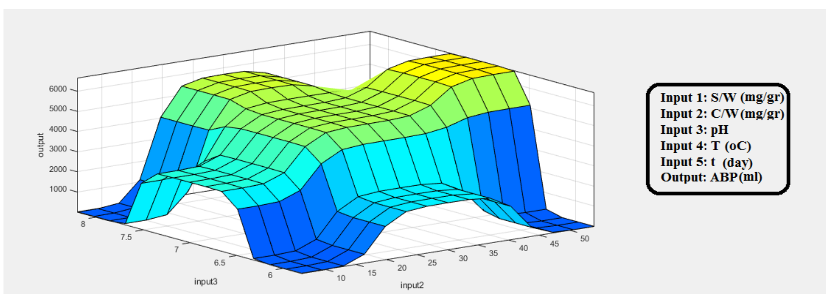
(b)


output
input4
input1
Input 1: S/W (mg/gr)
Input 2: C/W(mg/gr)
Input 3: pH
Input 4: T (oC)
Input 5: t (day)
Output: ABP(ml)

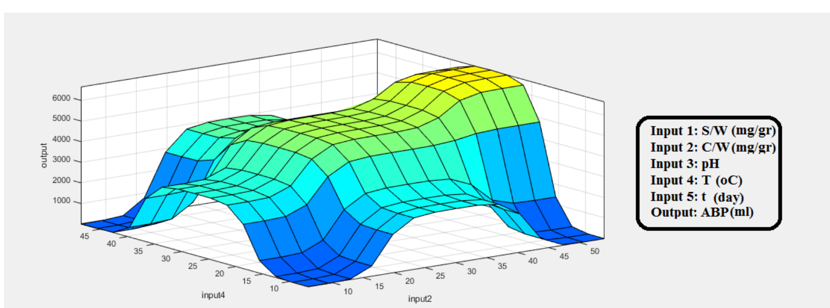
(c)


output
input5
input1
Input 1: S/W (mg/gr)
Input 2: C/W(mg/gr)
Input 3: pH
Input 4: T (oC)
Input 5: t (day)
Output: ABP(ml)

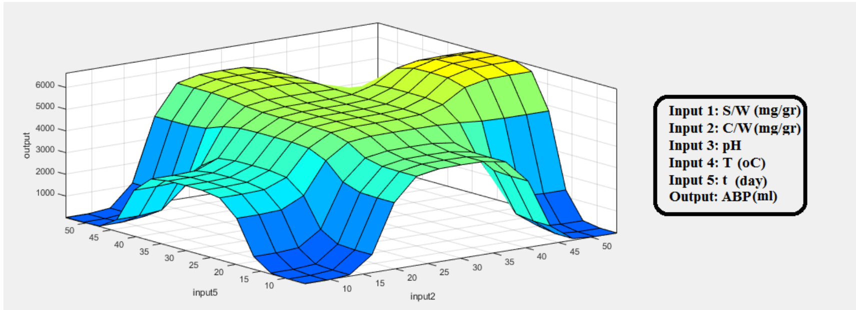
(d)


output
input3
input2
Input 1: S/W (mg/gr)
Input 2: C/W(mg/gr)
Input 3: pH
Input 4: T (oC)
Input 5: t (day)
Output: ABP(ml)

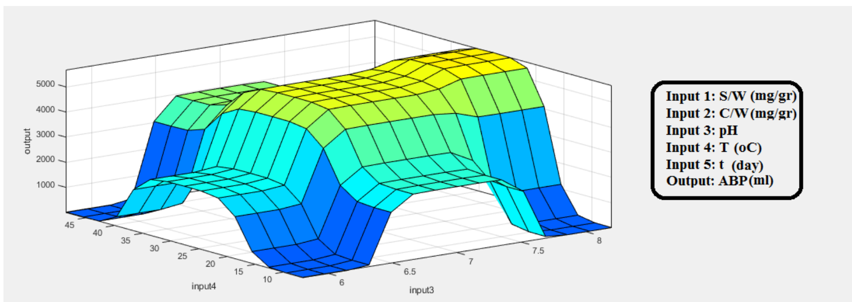
(e)


output
input4
input2
Input 1: S/W (mg/gr)
Input 2: C/W(mg/gr)
Input 3: pH
Input 4: T (oC)
Input 5: t (day)
Output: ABP(ml)

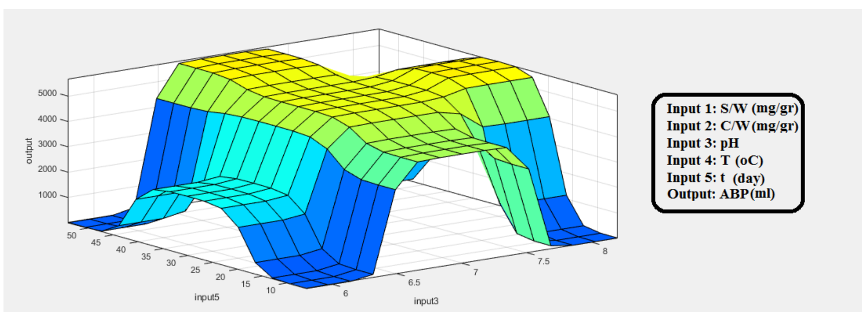
(f)



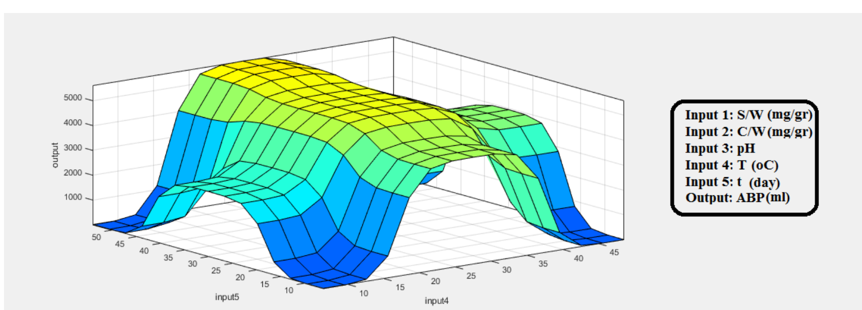
(g)



(h)



(i)



(j)

Fig. 13. The sensitive analysis of effective parameters in ANFIS model.

For creating DSS for smart controlling of bio-energy supplying, Petri Net modelling with combination of CCD-RSM optimization are utilized. The invented smart model for bio-energy management is depicted in Fig. 14. In the mentioned smart system, all effective parameters containing S/W, C/W, pH, T and t are set on optimum conditions and they check and modify sequentialy until to adjust in appropriate value throught a loop. Also, the mentioned concep first, evaluate S/W and T because of their significant effects on ABP in the parallel lines. Then, in the other series, pH (Souring control plan in the biogas system [48]) and S/W are controlled and adjusted. Finally, time of reaction as the least important factor is checked and justified. With application of Petri Net modelling according to Fig. 14, optimum conditions of biogas generation system can be controlled smartly.

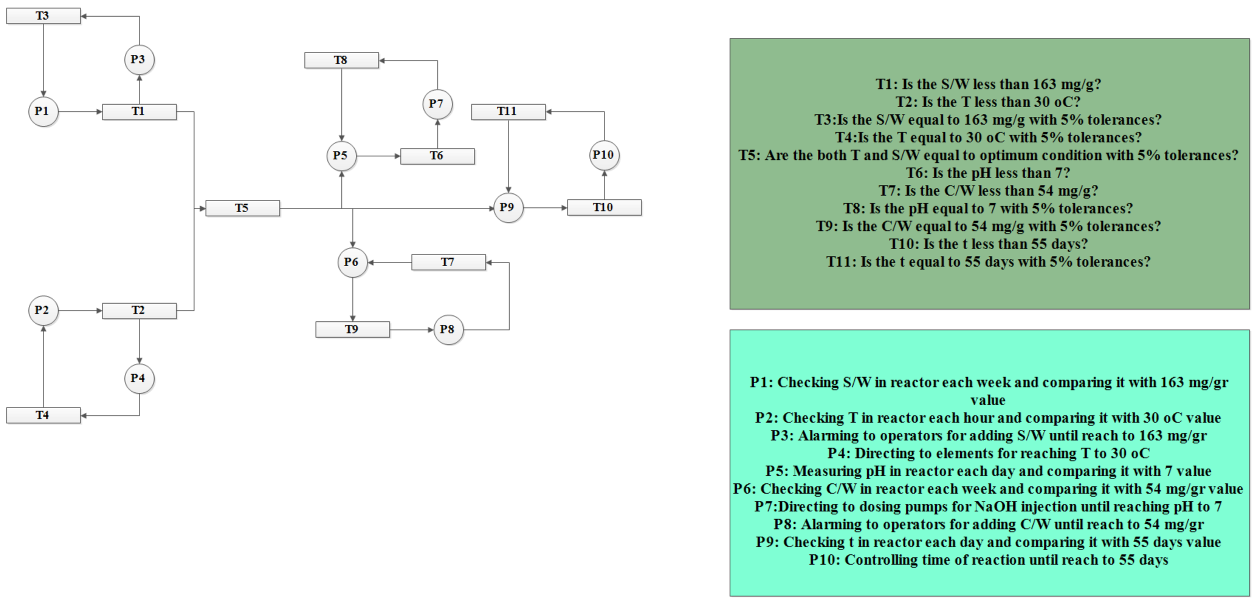


Fig. 14. The Petri Net modelling in present study.

3.3.Green building approach

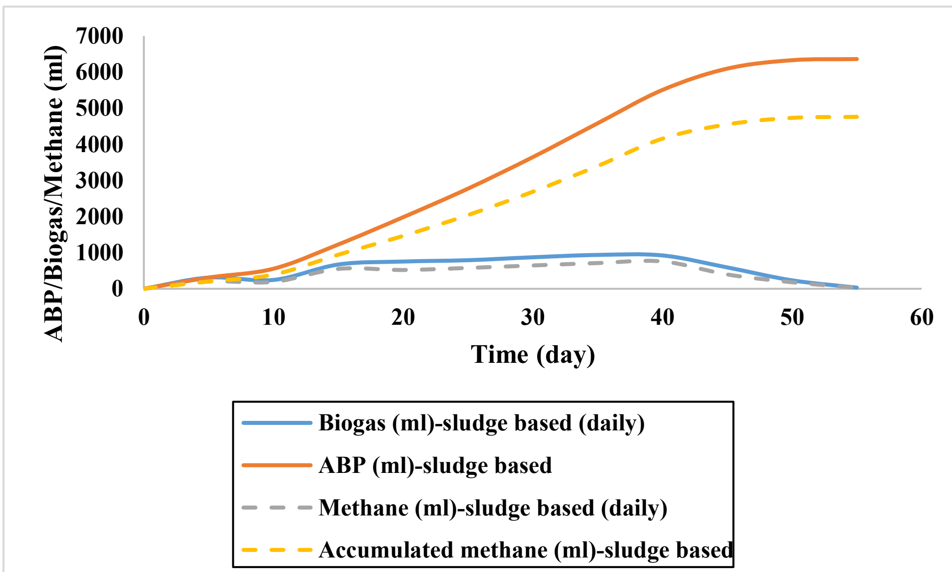
The results of present research have illustrated that with the role of sludge-based bacteria is more significant than *Clostridiales*. For scrutinizing the mentioned result, the experimental setup is appraised in a run without sludge and in the other one without *Clostridiales*. In each run, all effective parameters are set in optimum conditions, just, sludge and *Clostridiales* injecting are eliminated in determined tests. The output of daily and accumulated biogas/methane vs time variations is illustrated as per Fig. 15. According to Fig. 15, with application of sludge (without *Clostridiales*) biogas and methane production are around twice as much as biogas production with *Clostridiales* (without sludge) during 55-day retention time. One of the main achievements in this research was linked to presenting smart model for dynamic integrated management of sludge and *Clostridiales* bio-engines in the same time.

In the following, the recent investigations approved that 99% of biogas productions including methane and carbon dioxide [49-52]. Also, the nutrients (Nitrogen and phosphor) and active anaerobic microorganisms are provided by injected sludge from secondary clarifier tank in SBR.

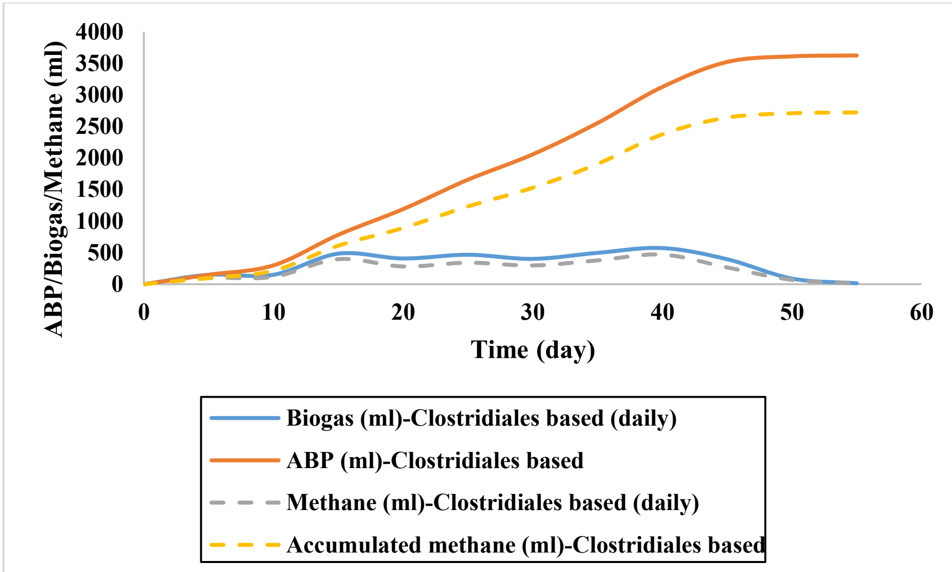
Thus, in the alone *Clostridiales* bioreactor the efficiency of anaerobic digester is reduced because of less nutrient and active microorganisms' values [53]. Likewise, the variation of TOC, COD and total alkaline of food wastes in both bioreactors (with Clostridiales and sludge) are illustrated in Fig. 16. According to this Fig., the organic matter digestion rate of sludge-based system is more than Clostridiales based bioreactor which is related to biodegradation ability of sludge-based microorganisms [54]. The alkalinity increasing in both reactors can be related to protein and amino acid biodegradation in the sequential reactions (Equation 3) [55]. While, in sludge-based system, rate of biodegradation is more than alone *Clostridiales* system and therefore, the amounts of total alkaline is increased in the declared system.

Equation 3

$NH_3 + H_2O + CO_2$ ® $NH_4^+ + HCO_3^-$

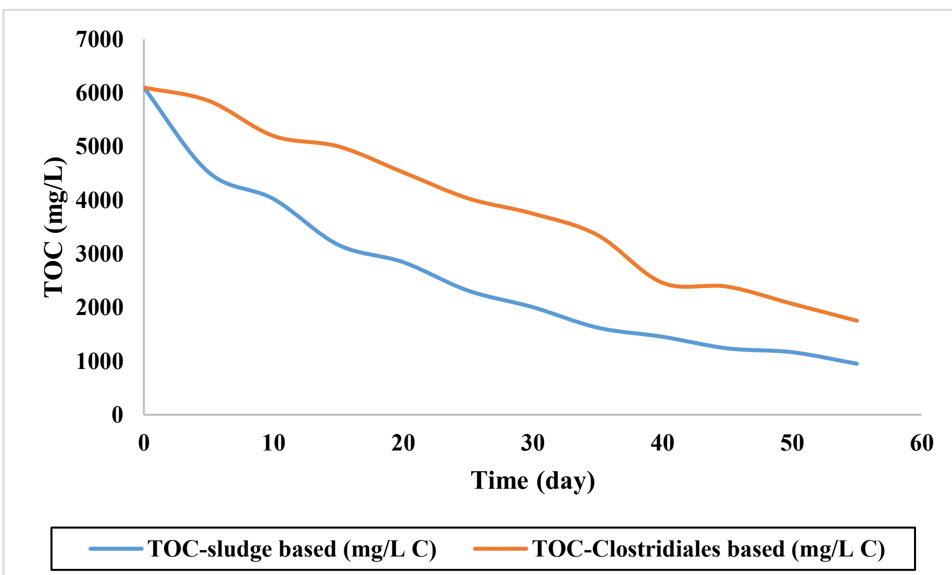


(a)

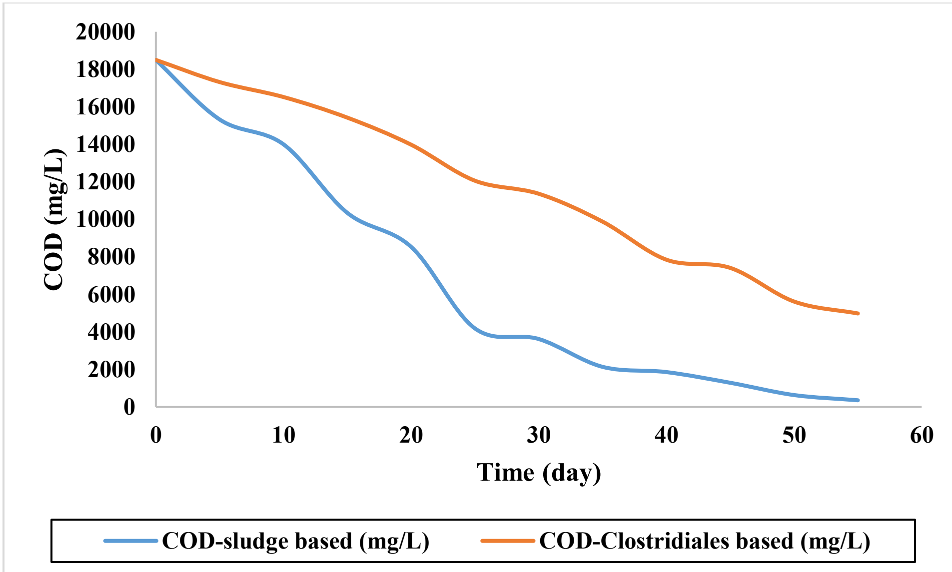


(b)

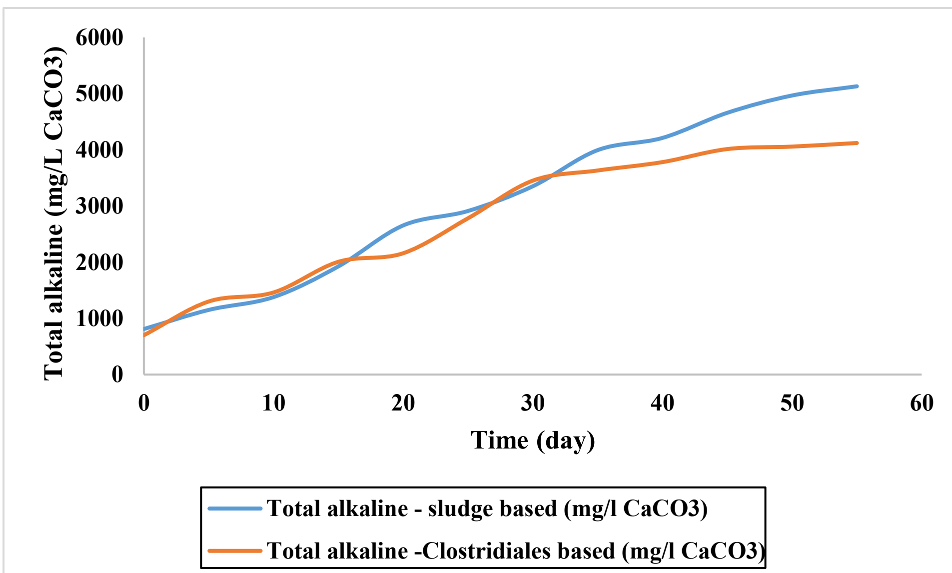
Fig. 15. Daily and accumulated biogas/methane production in (a) sludge based system and (b) Clostridiales based system.



(a)



(b)



(c)

Fig. 16. Efficiency of sludge and Clostridiales based systems for food waste biodegradation as per (a) TOC (b) COD and (c) total alkaline fluctuations.

As a result, it is clear that integration of SBR's sludge and Clostridiales can enhance the efficiency of bio-reactor in this study. Also, as can be seen in Table S.1, the integrated bioreactor has the acceptable efficiency in the low retention time and temperature which is affected by dual bio-engine activities in the same time [56]. In the last part of this research, pattern of energy production according to Circular Economy [57], Industry Ecology (IE) [58], Integrated Solid Waste Management (ISWM) [59] and Sustainable Development Goals (SDGs) [60] is illustrated in Fig.

17. Whereas, the digested food waste is biogas generation procedure can be useful as a fertilizer [61,62]. As per Fig. 17, the electrical energy generation of biogas system in present research can supply all energy demand based on Fig. 4. Also, the produced energy can be utilized for heat demand with 3051 MJ in 55-day (One operating duration) as a bio-energy supplying in green buildings. Finally, the digested organic materials with 310 mg/L COD value is appropriate for green environmental supporting in residential complex in the case study. Also, with considering to Fig. 4, the energy demand of case study is ranged 250 – 350 kwh/month and based on the achievements of present study, the available biogas energy is around 175 kwh/month (By 40% efficiency [63]). Therefore, around 50% of energy demand in the case study can be provided by biogas production in the present study.

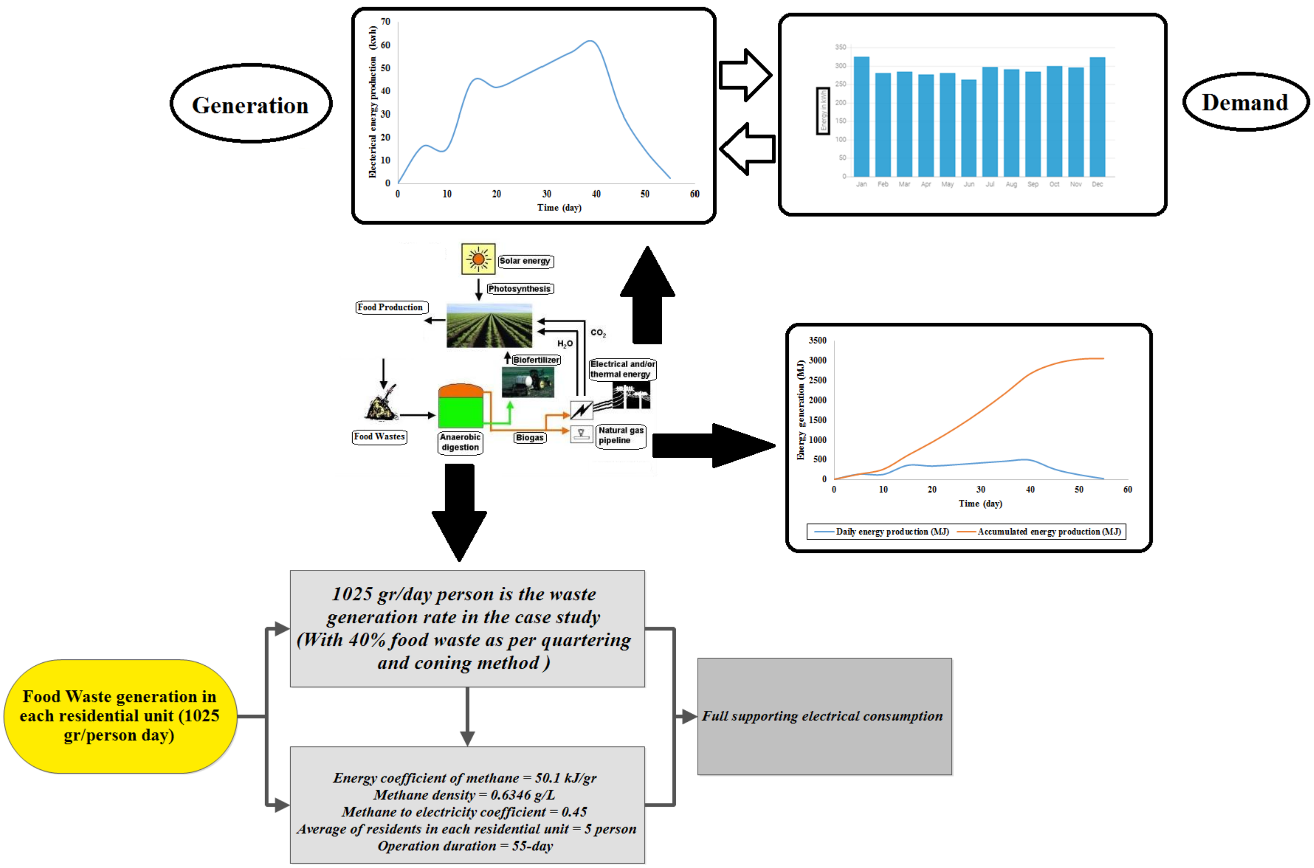


Fig. 17. The conceptual model of CE, ISWM and SDGs for implementation of green buildings in present investigation.

4. Conclusion

Food wastes have high level of variety in forming compositions containing proteins, fatty acids, carbohydrates, vitamins and other organic matters that they can product considerable biogas/methane through anaerobic digestion process. The declared technique is so beneficial for waste management and bio-energy supplying in the same time as a novel approach in green buildings. One of the main concerns about application of biological process in energy supplying is related to complexity of operation. Therefore, combination of smart controlling soft systems with biodegradation techniques can cover the weakness of bio-systems.

The main experimental, numerical and simulation practices in present research including:

- Preparing lab-scale setup for anaerobic digestion of food wastes with SBR's sludge and *Clostridiales* microorganisms.
- Optimizing and sensitive analyzing effective parameters by CCD-RSM technique.
- Implementation of smart system with four soft computing techniques containing RT, RF, ANN and ANFIS.
- Creating dynamic control system for adjusting effective parameters with Petri Net modelling.
- Assessment of SBR's sludge and *Clostridiales* on food waste anaerobic digestion in separated reactors.
- Presenting conceptual model as a CE platform for green buildings.

In the following, as per all experimental and computational efforts the main outcomes are listed below.

- Optimum values of S/W, C/W, pH, T and t are computed equal to 163 mg/g, 54 mg/g, 7, 30 °C and 55 days, respectively based on CCD-RSM optimization.
- The most significand effective factors on ABP/Methane production are S/W and T with less than 0.0001 P-value according to ANOVA calculations.
- The correlation coefficient of RT, RF, ANN and ANFIS computations are equal to 0.93, 0.87, 0.91 and 0.99 values. Therefore, ANFIS model has the best precision for ABP forecasting in DSS.
- In the Petri Net model, controlling S/W and T is prioritized in comparison of other parameters because of their P-value and F-value amounts.
- The efficiency of SBR's sludge is more than *Clostridiales* based bioreactor because of nutrient availability and activity of microorganisms. In the same conditions, methane production of sludge-based bioreactor 42% is more than other one.
- With performing bio-energy supplying 381 kwh (3051 MJ) can be obtained that is enough for electrical energy demand or heat energy consumption.

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