Appendix A

Preparation of BG11 media

In present study, freshwater microalgae strains, *C. pyrenoidosa* (NCIM 2738), *C. protothecoides* (NCIM 5527), *C. minutissima* (procured from Indian Agricultural Research Institute, India) and marine microalgae strains, *Dunaliella* sp. (BDU 10113) and *C. vulgaris* (BDUG D003) were cultivated in BG-11 medium. BG-11 is most widely used media for microalgae system. The composition of BG-11 medium has been presented in Table A.1. The 100 mL aliquots of the prepared BG-11 medium were transferred into the 250 mL flasks sealed with cotton stoppers. After that, these aliquots were autoclaved for 30 minutes at 121°C and 15 psi. After autoclaving and cooling, the pH of each aliquot was maintained.

Table A.1 BG11 media composition.

Component	**Amount (per liter)**
$NaNO_3$	1.5 g
$MgSO_4 \cdot 7H_2O$	0.075 g
K_2HPO_4	0.04 g
Na_2CO_3	0.02 g
$CaCl_2 \cdot 2H_2O$	0.036 g
Citric acid	0.006 g
Ferric ammonium citrate	0.006 g
EDTA (disodium salt)	0.001 g
Trace metal mix	1.0 ml
Distilled water	1.0 L
Trace metals	
$MnCl_2 \cdot 4H_2O$	1.81 g
H_3BO_3	2.86 g
$NaMoO_4 \cdot 2H_2O$	0.39 g
$ZnSO_4 \cdot 7H_2O$	0.222 g
$CuSO_4 \cdot 5H_2O$	0.079 g
$Co(NO_3)_2 \cdot 6H_2O$	49.4 mg

Preparation of MBG11 media

To perform desalination experiments, MBG-11 is prepared by adding K in replacement of Na. Excluding Na, other nutrients are maintained identical to BG-11 composition. The composition of MBG-11 (g L^{-1}) has been presented in Table A.2.

Table A.2 MBG-11 media composition.

Chemical	g L^{-1}
KNO_3	1.78
$K_2HPO_4.3H_2O$	0.04
$CaCO_3$	0.009
$MgSO_4.7H_2O$	0.075
$CaNO_3.2H_2O$	0.034
EDTA-K_2	0.001
Fe $(NH_3)_2$Citrate	0.006
Citric acid	0.006
Trace elements	1 mL

Appendix B

Preparation of dry cell weight (DCW) calibration curve of fresh and marine microalgae cultures

1. To prepare specific DCW calibration curve, all fresh and marine microalgae cultures were grown to the exponential phase.
2. The 50 mL cell culture aliquotes of different optical density (OD) were prepared.
3. The prepared samples were centrifuged at 5000g for 10 minutes to pellet the cells.
4. After pelleting, cultures were washed twice through centrifugation using distilled water (DW) to remove the residual nutrients and further resuspended in DW to maintain 5 mL volume.
5. These resuspended cultures were further transferred into different pre-wieghed alumunium foil cups (W_1) and further dried in a hot air oven at 60 °C for 6 h.
6. After drying, all the cups containing dried biomass were reweighed (W_2) to obtain the final biomass weight by substracting W_2 from W_1.
7. Finally, calibration curves were constructed by plotting the DCW against the corresponding OD values for individual samples.
8. To prevent contamination, sterile conditions were maintained throughout the procedure and data was measured accurately.

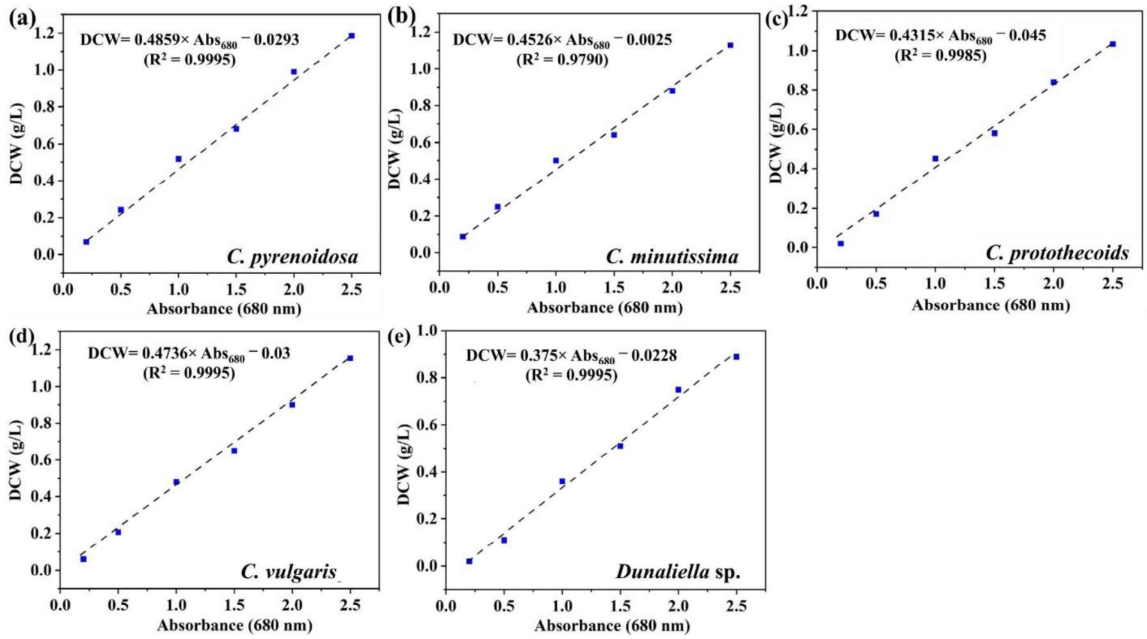

Figure B.1 Dry cell weight calibration curve of (a) *Chlorella pyrenoidosa* (b) *Chlorella minutissima* (c) *Chlorella protothecoides* (d) *Chlorella vulgaris* (e) *Dunaliella* sp. culture.

Appendix C

Lipid estimation

1. Lipid extraction from dried algal powder was performed using Bligh and Dyer's method.
2. For each 1 mL of microalgae sample, 3.75 mL chloroform: methanol (2:1, v/v) was added and vortexed well.

   The table below shows proportions for different volume of sample:

Sample	0.2 mL	0.5 mL	1 mL	1.5 mL	2 mL	3.5 mL
1:2 $CHCl_3$: MeOH	0.75	1.9	3.75	5.7	7.5	13.125
$CHCl_3$	0.25	0.625	1.25	1.875	2.5	4.375
dH_2O	0.25	0.625	1.25	1.875	2.5	4.375
Total volume	1.45	3.65	7.25	10.95	14.5	25.375

3. Further, 1.25 ml $CHCl_3$ was added and vortexed well.
4. Finally, 1.25 ml dH_2O was added and vortexed well.
5. The vortexed sample was centrifuged in table-top centrifuge at 1000 RPM for 10 min (room temperature) to provide two phase separation as aqueous top and organic bottom.
6. Further, pasteur pipette is inserted through the upper phase with gentle positive pressure so that aqueous top does not get inserted into the pipette tip. When, pipette tip reached at the bottom of the tube, the bottom phase is carefully rejected through the pipette without disturbing interface or upper phase. Nearly, 90% of bottom phase was recovered through this process.
7. The organic layer containing lipid and chloroform was collected and total volume was recorded (V_t). The known volume of organic layer was transferred to a clean pre-weighed vial (W_1).
8. The sample was dried in hot air oven at 80 °C for 50 min. The final weight of the lipid containing dried vial was noted (W_2).

9. The lipid content is expressed as a percentage of dried algal biomass and calculated according to below equation:

$$Lipid\ content\ (LC\ \%) = \frac{(\mathrm{W_1}-\mathrm{W_2})\times \mathrm{V_t}}{\mathrm{V_a}} \times 100$$

Where, W_1 and W_2 are the initial and final weights of the vials in mg, respectively. V_t and V_a are total volumes of the organic layer and aliquot in mL.

Appendix D

Transesterification to fatty acid methyl esters

1. Following lipid extraction, the tube containing dried lipids (initially mixed with $CHCl_3$ fraction) was added with 3 mL methanol containing 5%(v/v) H_2SO_4.
2. Tubes were vortexed for 5 s.
3. After that, samples were incubated in a water bath or block heater for 3 h at 70 °C. Further, samples were checked at every 30 min to prevent boiling and whether tubes were properly closed or not.
4. Through chemical reaction, fatty acids were methylated to their respective FAMEs.
5. Samples were cooled to room temperature and further, 3 ml MilliQ water and 3 ml n-hexane was added.
6. Sample was vortexed for 5 sec and mixed in a test tube rotator for 15 min.
7. Sample was centrifuged at 1,200 × g for 5 s.
8. The 2 ml of the top phase (hexane) was collected and pipette out in a glass tube.
9. The collected hexane phase was washed with 2 ml MilliQ water.
10. The hexane phase was revortexed for 5sec and further centrifuged at 1,200 × g for 5 min.
11. After this step, samples were stored at – 20 °C under nitrogen gas atmosphere.
12. Further, FAMEs quantification was conducted using gas chromatography – mass spectrophotometry (GC – MS).

Appendix E

Chemical oxygen demand (COD) estimation

Apparatus: Analytical weighing balance with accuracy of 0.0001 g, glassware, Uniphos COD digester, muffle furnace, culture tubes, Uniphos COD analyzer.

Reagents:

1. Reagent water: Distilled or deionized water, free of the analyte of interest. ASTM Type II or equivalent.
2. Reagent A: Add 2.3 g $K_2Cr_2O_7$, 20 mL conc. H_2SO_4 and 3.34 $HgSO_4$ to 50 mL of reagent water, cool and dilute to 100 mL.
3. Reagent B: Add 1 g Ag_2SO_4 to a 100 ml of conc.H_2SO_4, Stir until dissolved.
4. Sampler wash solution: Add 250 mL of conc. H2SO4 to 250 mL of reagent water.
5. Stock potassium hydrogen phthalate standard: Dissolve 0.425 g potassium hydrogen phthalate (K H P) in 400 mL of reagent water and dilute to 500 mL. 1 mL = 1 mg COD.

Calibration and standardization:

1. To calibrate the analyser blank was placed at zero value.
2. The 1000 mg L^{-1} KHP standard was placed and maintain the analyser to read 1000 mg L^{-1}.

Measurement:

1. Initially, all culture tubes were washed with 20% H_2SO_4 and then caps were closed.
2. Approximately 100 mg $HgSO_4$ solution was transferred in a 16 ×75 mm tubes.
3. Further, 1 mL of sample, standard or blank were pipetted out into 16 ×75 mm tubes.
4. 0.6 mL of reagent A solution was added to the 16 ×75 mm tubes.
5. After that, 1.4 mL of reagent B solution was transferred to the 16 ×75 mm tubes.
6. Tubes were tightly capped and shaked to mix layer.

7. These tubes were placed into a Uniphos digester at 150 °C and heated for 2h.

8. After removing out of digester, tubes were cooled.

9. Standards, blanks and samples were further placed in a culture tube stand.

10. The analyzer was calibrated with a known standard and all samples were measured.

Interferences:

The Cl^- ion present in sample may be oxidized by $K_2Cr_2O_7$ resulting positive interference. Therefore, $HgSO_4$ is added to the tubes to nullify the Cl^- ion interference. The amount of $HgSO_4$ is enough to suppress 10000 mg L^{-1} of Cl^- ion.

Safety:

Caution must be taken to handle extremely hazardous materials.

Appendix F

Electric conductivity measurement

Apparatus: Conductivity meter with resolution 0.01 / 0.1mS, reciprocating shaker, deionized/distilled water.

Calibration:

Initially the conductivity meter was prepared to use according to the manufacture's direction.

Conductivity standard solution (KCl solution with 0.147dS m^{-1}) was used to calibrate the conductivity meter for specified range of measurement.

Measurement:

1. Probe was rinsed with distilled or deionized water.
2. The appropriate range of conductivity was selected, starting with highest range and then gradually down. The conductivity of the sample was noted. If the reading lies in the lower 10% of the range, then switched to the next lower range. If the conductivity range exceeds beyond instrument range, sample is diluted.
3. The probe is rinsed with distilled or deionized water and step 4 is repeated until finished.

Appendix G

Deep neural network code to develop Conv 1D-LSTM model for prediction and verification of TGA data for de-oiled microalgae pyrolysis.

```
#python libs
 import pandas as pd
 import numpy as np
 import matplotlib.pyplot as plt
 #sklearn APIs
 from sklearn.model_selection import train_test_split
 from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
 from sklearn import preprocessing
 #keras APIs
 from keras.models import Sequential,Model,save_model,load_model
 from keras.layers import Dense,InputLayer,Conv1D,MaxPooling1D
 from keras.layers import LSTM,Flatten
 from keras import regularizers
 from keras.optimizers import Adam
 from keras.metrics import RootMeanSquaredError,MeanAbsolutePercentageError
 from keras.utils import plot_model
 #data loading from flat files.
 df = pd.read_csv('../../Data/TGA10/Data_TGA10.csv')
 #data outlook
 df.describe()
 #normalization
names = df.columns
 d = preprocessing.normalize(df,axis=0)
 scaled_df = pd.DataFrame(d,columns=names)
 scaled_df.head()
 #
 # data preprocessing (separation of input data and output data)
 X=scaled_df.drop("Massloss",axis=1)
 Y=scaled_df["Massloss"]
 #end
 # Hybrid DNN model (CNN-RNN-MLP) designing
 model=Sequential(name='CNN_Sequential_model')
 #inpput layer
 model.add(Conv1D(32, name="Input_layer1_Conv1D",
kernel_size=2,activation='PReLU',strides=1,
padding="valid",use_bias=True,input_shape=(X_train.shape[1],1)))
 model.add(MaxPooling1D(1, name='Pooling_Operation_1',padding='valid'))
 #
 model.add(Conv1D(12, name="Hidden_layer2_Conv1D",kernel_size=1))
 model.add(MaxPooling1D(1, name='Pooling_Operation_2',padding='valid'))
 #LeakyReLU
```

```
model.add(LSTM(32,name='LSTM_FC_layer',activation="tanh",recurrent_activation="sigm
oid"))

model.add(Dense(16,name='Hidden_dense_layer1',use_bias=True,activation='PReLU',kernel
_reg
 ularizer=regularizers.l2(0.01)))

model.add(Dense(4,name='Hidden_dense_layer2',use_bias=True,activation='PReLU',kernel_
regul
 arizer=regularizers.l2(0.01)))
 model.add(Dense(1,name='Output_layer',activation='linear'))
 model.summary()
 # do not change this code
 #model opimization and compilation
model.compile(optimizer = Adam(learning_rate=0.001), loss='mse',metrics=['mae','mape'])
 # model fitting
 lstm=model.fit(X_train,Y_train,validation_data=(X_val, Y_val),epochs
=120,batch_size=20,shuffle=True)
 #model.run_eagerly=True
#evaluate model
 model_score=model.evaluate(X_train,Y_train,verbose=1)
 model_score
 # check for loss value of the model, it should be minimum
 font1 = {'family':'Times New Roman','color':'black','size':24}
 font2 = {'family':'Times New Roman','color':'darkred','size':22}
 plt.rcdefaults()
 plt.grid(visible=None)
 plt.grid(False)
 ax=plt.gca()
 ax.tick_params(which='both', width=3)
 ax.tick_params(which='major', length=20, color='b')
 ax.tick_params(which='minor', length=10, color='r')
 plt.rcParams['figure.figsize']=(10,6)
 plt.plot(lstm.history['loss'],linewidth = '3.5')
 plt.plot(lstm.history['val_loss'],linewidth = '3.5')
 plt.title('Model loss',fontdict=font1)
 plt.ylabel('MSE',fontdict=font2)
 plt.xlabel('Epochs',fontdict=font2)
 plt.legend(['Training Loss', 'Validation Loss'], loc='upper right',fontsize=22)
 plt.show()
 predict_values=model.predict(X_test).flatten()
 # R2 value
 r2_score(Y_test, predict_values)
 #RMSE, MSE and MAE
 mse_Conv=mean_squared_error(Y_test,predict_values)
 mae_Conv=mean_absolute_error(Y_test,predict_values)
 rmse_Conv=mean_squared_error(Y_test,predict_values,squared=False)
 print("Mean squared error (MSE) from neural network: ", mse_Conv)
 print("Mean squared error (RMSE) from neural network: ", rmse_Conv)
```

```
print("Mean absolute error (MAE) from neural network: ", mae_Conv)
prediction_conv=pd.DataFrame(data={'Prediction': predict_values,'Experimental': Y_test})
#prediction_conv.sort_values(by=['Actual'])
sorted_df = prediction_conv.sort_values(by = 'Experimental',ascending=False)
sorted_df.to_csv('../../Data/TGA10/328321641/Prediction_TGA10_120_Final.csv')
sorted_df
#prediction_conv
#prepare a dataframe to merge with predicated result to draw a chart later. it is like temperature
vs
true values and
#predicted values
X_test_sorted=X_test.sort_values(by='Temperature')
X_test_sorted.to_csv('../../Data/328321641/TGA10/X_Test_TGA10_120_final.csv')
#Y_test_sorted
```

Appendix H

MATLAB code for ANN-MOGA based hymethane syngas emission process optimization

```
% Solvean Input-Output Fitting problem with a Neural Network
 % Script generated by Neural Fitting app
 % Created 18-Jun-2023 23:44:46
 %
 % This script assumes these variables are defined:
 %
 % input-input data.
 % output-target data.
 x=input';
 t=output';
 % Choose a Training Function
 % For a list of all training functions type: help nntrain
 % 'trainlm' is usually fastest.
 % 'trainbr' takes longer but may be better for challenging problems.
 % 'trainscg' uses less memory. Suitable in low memory situations.
 trainFcn = 'trainlm'; % Levenberg-Marquardt backpropagation.
 % Create a Fitting Network
 hidden Layer Size =10;
 net = fitnet(hiddenLayerSize, trainFcn);
 % Setup Division of Data for Training, Validation, Testing
 net.divideParam.trainRatio=70/100;
 net.divideParam.valRatio=15/100;
 net.divideParam.testRatio=15/100;
% Train the Network
 [net,tr] = train(net,x,t);
 %Test the Network
 y = net(x);
 e = gsubtract(t,y);
```

```
performance = perform(net,t,y)
% View the Network
%view(net)
%Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotfit(net,x,t)
% Define the input ranges to search over
blending_ratio_range=0:100;
heating_rate_range=5:25;
fitnessFunction=@(x)-sim(net, x');
nvars = 2;
LB=[min(blending_ratio_range), min(heating_rate_range)];
UB=[max(blending_ratio_range), max(heating_range_range)];
options=optimoptions ('gamultiobj', 'Display', 'off'); %Hide the display
%options=optimoptions('gamultiobj', 'Display', 'off', 'MaxObjectiveEvaluations',1000);
options.PopulationSize=100; % Population size (you can adjust this as needed)
options.MaxGenerations=1000;% Maximum number of generations(you can adjust this as
needed)
% Run MOGA
[xOpt, fOpt]=gamultiobj(fitnessFunction,nvars, [], [], [], [], LB, UB, options);
% Display the results
%disp('Optimization Complete');
%disp('OptimalValues of Y1,Y2,and Y3:');
%disp(fOpt);
%disp(['Optimal InputParameters-blending_ratio: ',num2str(xOpt(:,1)')]);
%disp(['Optimal InputParameters-heating_rate: ',num2str(xOpt(:,2)')]);
```

```
disp('Optimization Complete');
disp('Maximized Values of Y1,Y2,and Y3:');
disp(-fOpt);
disp(['Optimal Input Parameters-blending _ratio: ',num2str(xOpt(:,1)')]);
disp(['Optimal InputParameters-heating_rate: ',num2str(xOpt(:,2)')]);
num2str(xOpt(:,1))
figure;
plot3(fOpt(:,1), fOpt(:,2), fOpt(:,3), 'o');
title('Pareto Front');
xlabel('Y1');
ylabel('Y2');
zlabel('Y3');
grid on;
plot3(-fOpt(:,1),-fOpt(:,2),-fOpt(:,3), 'bo');
xlabel('Objective 1');
ylabel('Objective 2');
zlabel('Objective 3');
title('Pareto Front');
figure;
plot3(-fOpt(:,1),-fOpt(:,2),-fOpt(:,3), 'b-');
hold on;
scatter3(-fOpt(:,1),-fOpt(:,2),-fOpt(:,3), 'ro', 'LineWidth',1.5);
xlabel('Objective 1');
ylabel('Objective 2');
zlabel('Objective 3');
title('Pareto Front');
legend('Pareto Front', 'Optimal Points');
fitness_func=@(x)-net(x');
nvars=2;
LB=[min(blending_ratio_range), min(heating_rate_range)];
```

```
UB=[max(blending_ratio_range), max(heating_rate_range)];
% Define the genetic algorithm options
options=optimoptions('ga', ...
'PopulationSize',200, ...
'CrossoverFraction',0.8, ...
'EliteCount',10, ...
'MaxGenerations',1000, ...
'FunctionTolerance',1e-4, ...
'PlotFcn',{@gaplotdistance,@gaplotrange},...
'MutationFcn',{@mutationadaptfeasible,0.01},...
'UseParallel', true);
% Run the genetic algorithm to find the optimal input values
[optimal_inputs,max_production]=ga(fitness_func,nvars, [], [], [], [],LB,UB, [],options);
% Display the optimal input combination and resulting production
fprintf('Optimal blending ratio:%f\n',optimal_inputs(1));
fprintf('Optimal heating rate:%f\n',optimal_inputs(2));
fprintf('Max Hymethane carrying ratio1:%f\n',-max_production);
fprintf('Max Hymethane carrying ratio2:%f\n',-max_production);
fprintf('Max Hymethane carrying ratio3:%f\n',-max_production);
disp(['Optimal InputParameters-Blending_ratio: ',num2str(xOpt(:,1), '%s\n')]);
```

Appendix I

List of Publications

Journals

1. **Shweta Rawat**, Agendra Gangwar, Sanjay Kumar (2024c) “Semi-continuous cultivation of microalgae to treat coal mine effluent in pilot scale: Nutrient removal, biodesalination and fatty acid composition analysis”. Journal of water process engineering, 106271.
2. **Shweta Rawat**, Alok Kumar Singh, Jyoti Prasad Chakraborty and Sanjay Kumar (2024b) “Characterization and mechanism elucidation of high-quality bio-oil production from co-pyrolysis of waste low-rank coal fines and de-oiled microalgae biomass using bimetallic (Cu-Cr) ZSM-5 catalyst”. Journal of Environmental Chemical Engineering, 113046.
3. **Shweta Rawat** and Sanjay Kumar (2024a) “Multi objective genetic algorithm approach for enhanced cumulative hydrogen and methane rich syngas emission through co-pyrolysis of de-oiled microalgae and coal blending”. Renewable Energy, 120264.
4. **Shweta Rawat** and Sanjay Kumar (2023c) “Thermal response estimation of de-oiled fresh and marine microalgae based on pyrolysis kinetic studies and deep neural network modeling”. BioEnergy Research, 1-17.
5. **Shweta Rawat**, Akhil Rautela, Indrajeet Yadav, Sibashis Misra, and Sanjay Kumar (2023b) “A Comprehensive Review on Enhanced Biohydrogen Production: Pretreatment, applied strategies, techno-economic assessment and future perspective”. BioEnergy Research, 1-24.
6. **Shweta Rawat** and Sanjay Kumar (2023a) “Performance enhancement of value-added microalgae biomass blended coal composites using statistical approach: characterization and thermal behavior assessment”. Biomass conversion & biorefinery, 1-22.
7. **Shweta Rawat** and Sanjay Kumar (2021) “Critical review on processing technologies and economic aspect of bio-coal briquette production”, Preparative Biochemistry & Biotechnology, 855-871.
8. Agendra Gangwar, **Shweta Rawat**, Akhil Rautela, Indrajeet Yadav, Anushka Singh, and Sanjay Kumar (2023) “Current advances in Produced Water Treatment Technologies: A perspective of techno-economic analysis and life cycle assessment”. Environment, Development and Sustainability, 1-35.
9. Indrajeet Yadav, Akhil Rautela, Agendra Gangwar, Lokesh Wagadre, **Shweta Rawat** and Sanjay Kumar (2023) “Enhancement of Isoprene Production in Engineered

Synechococcus elongatus UTEX 2973 by Metabolic Pathway Inhibition and Machine Learning-Based Optimization Strategy. Bioresource Technology, 387, 129677.

10. Geetanjali, **Shweta Rawat**, Radha Rani, and Sanjay Kumar (2023) “Kinetic modeling for miniaturize single-chambered microbial fuel cell: effects of biochemical reaction on its performance”. Environmental Science and Pollution Research, 1-10.
11. Nirakar Pradhan, Sanjay Kumar, Rangabhashiyam Selvasembian, **Shweta Rawat**, Agendra Gangwar, R. Senthamizh, Yuk Kit Yuen, Joyabrata Mal (2022) “Emerging trends in the pretreatment of microalgal biomass and recovery of value-added products: A review”. Bioresource Technology, 369, 1283965.

Book chapters

1. Akhil Rautela, **Shweta Rawat**, Indrajeet Yadav, Agendra Gangwar and Sanjay Kumar (2023) “Process integration opportunities applied to microalgae biomass production.” In Microalgae-Based Systems: Process Integration and Process Intensification Approaches, pp. 183-210. De Gruyter.
2. Indrajeet Yadav, Akhil Rautela, **Shweta Rawat**, Ajay Kumar Namdeo and Sanjay Kumar (2023) “Metabolic engineering of yeast for advanced biofuel production.” In Advances in Yeast Biotechnology for Biofuels and Sustainability, pp. 73-97. Elsevier.

Appendix J

<u>Conferences/workshops</u>

1. **Shweta Rawat** and Sanjay Kumar (2023) Comparative and dynamic analysis of pyrolytic behavior, kinetics and in-situ gas emission from co-pyrolysis of coal and de-oiled microalgae (AFMI-2023) organized by IITBHU, Varanasi. (November 29-December 3,2023) (**Best oral presentation**).
2. **Shweta Rawat** and Sanjay Kumar (2022) Investigations on mechanical and thermal performance of wastewater grown microalgae blended coal briquettes as Green coal (VII SEEC- 2022) organized by IITBHU, Varanasi. (December 16-18,2022) (Oral presentation).
3. **Shweta Rawat** and Sanjay Kumar (2022) The feasibility study of green microalgae assisted coal mine effluent desalination. Biosangam 2022. 17, An International Conference Emerging Trends in Biotechnology, MNNIT Allahabad. (March 10-12, 2022) (Oral presentation).
4. **Shweta Rawat** and Sanjay Kumar (2021) Process development and performance assessment of wastewater grown microalgae-coal densification. 4th International Conference on Opencast Mining Technology & Sustainability (ICOMS-2021) organized by Northern Coalfields Limited, Singrauli in association with IIT BHU. (December 13-14, 2021) (**Best poster presentation award**).