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ARTIFICIAL NEURAL NETWORKS BASED MODELING AND OPTIMIZATION OF THERMOCHEMICAL CONVERSION OF BIOMASS

By

Ahmed Abdelgawad Aly Abdelgawad Mady

A Thesis Submitted to the Faculty of Engineering at Cairo University in Partial Fulfillment of the Requirements for the Degree of

MASTER OF SCIENCE

In

Chemical Engineering

FACULTY OF ENGINEERING, CAIRO UNIVERSITY GIZA, EGYPT 2022

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Under the Supervision of

Prof. Dr. Mohamed Hanafy	Dr. Ahmed Wafiq
Professor of Chemical Engineering	Lecturer
Chemical Engineering Department	Chemical Engineering Department
Faculty of Engineering, Cairo University	Faculty of Engineering, Cairo University

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Approved by the Examining Committee:

Prof. Dr. Mohamed Hanafy
Professor of Chemical Engineering, Cairo University

Prof. Dr. Magdy Abadir
Professor of Chemical Engineering, Cairo University

Prof. Dr. Abdelghani Abo-Elnour
Professor of Chemical Engineering, National Research Center

FACULTY OF ENGINEERING, CAIRO UNIVERSITY GIZA, EGYPT 2022 **Engineer's Name:** Ahmed Abdelgawad Aly Abdelgawad Mady

Date of Birth: 03/11/1994 **Nationality:** Egyptian

E-mail: ahmed_mady_stu@yahoo.com

Phone: 01022188356

Address: 36 darmasr 6th of October, Giza.

Registration Date: 01/10/2018 **Awarding Date:** / /2022

Degree: Master of Science **Department:** Chemical Engineering

Supervisors:

Prof. Mohamed Hanafy Dr. Ahmad Wafiq

Examiners:

Prof. Dr. Mohamed Hanafy (Thesis Main Advisor)

Professor of Chemical Engineering, Cairo University

Prof. Dr. Magdy Abadir (Internal Examiner)
Professor of Chemical Engineering, Cairo University

Prof. Dr. Abdelghani Abo-Elnour (External Examiner)Professor of Chemical Engineering, National Research Center

Title of Thesis:

ARTIFICIAL NEURAL NETWORKS BASED MODELING AND OPTIMIZATION OF THERMOCHEMICAL CONVERSION OF BIOMASS

Key Words:

Deep learning, Machine learning, Combustion, Pyrolysis, Gasification.

Summary:

Biomass is considered one of the most promising and feasible renewable energy sources. Over time, the exploitation of biomass feedstock for various industries has been grown significantly. Most experimental techniques, however, require equipment that is extremely complex and costly. In this research, a novel approach aiming to predict the most desirable outputs of different biomass thermochemical conversion processes has been adopted.

The main goal of this study is to utilize the machine learning techniques specifically deep learning in the field of biomass energy recovery through the development of artificial neural network models that can predict the higher heating value of biomass feedstock, lower heating value of gasification product, bio-oil and bio-char weight percentages for fast and slow pyrolysis respectively. The main input parameters used are obtained using both proximate and ultimate analysis as well as operating conditions for gasification and pyrolysis. This study also introduces deep learning aside with optimization as a magic tool for identifying different biomass feedstock that have a high potentiality for further processing technology or investigation.

Disclaimer

I hereby declare that this thesis is my own original work and that no part of it has been submitted for a degree qualification at any other university or institute.

I further declare that I have appropriately acknowledged all sources used and have cited them in the references section.

Name: Ahmed Abdelgawad Aly Abdelgawad Mady Date: / /2022

Signature:

Dedication

I would like to dedicate this thesis with sincere gratitude to my parents for their love, support and encouragement throughout my life. I would also like to dedicate this message to my dear sisters and colleagues who have always stood by me and supported me.

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My deep gratitude to **Prof. Dr. Mohamed Hanafy** due to his support during the different stages of carrying out this research, his guidance and instructions not only enriched my academic knowledge, but also helped me to come up with a thorough perspective as a young researcher who is seeking to contribute to more research studies.

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Table of Contents

DISCLAIMER	I
DEDICATION	II
ACKNOWLEDGMENTS	III
TABLE OF CONTENTS	IV
LIST OF TABLES	VI
LIST OF FIGURES	VIII
NOMENCLATURE	X
ABSTRACT	XI
CHAPTER1 INTRODUCTION	1
CHAPTER2 LITERATURE REVIEW	
2.1 CHARACTERISTICS OF BIOMASS FUELS	ERSION
2.2.1 Combustion.	
2.2.2 Pyrolysis	9
2.2.3 Gasification.	
2.3 OVERVIEW OF DEEP LEARNING BASIC CONCEPTS, STRUCTURE AN MATHEMATICS OF ARTIFICIAL NEURAL NETWORKS	
2.3.1 Artificial intelligence (AI)	
2.4 REVIEW OF RELEVANT BIOMASS ENERGY RECOVERY MODELING	
2.4.1 Combustion.	
2.4.2 Gasification	
2.5 COMMON RESEARCH GAPS	
2.6 SIGNIFICANCE TESTS FOR NEURAL NETWORKS	
2.6.1 Various techniques for evaluating variable significance in A	ANNs 35
CHAPTER3 METHODOLOGY	37
3.1 Procedure	38
3.1.1 Data preprocessing	
3.1.2 Model Training & Optimization	
3.1.3 Evaluation metrics	
3.1.5 Gasification	
3.1.6 Fast pyrolysis	
3.1.7 Slow Pyrolysis	
CHAPTER4: RESULTS AND DISCUSSIONS	53
4.1 COMBUSTION	
4.1.1 Results	
4.1.2 Discussion	
4.2.1 Results	
4.2.2 Discussion.	

4.3 FAST PYROLYSIS	61
4.3.1 Results	61
4.3.2 Discussion	67
4.4 Slow pyrolysis	68
4.4.1 Results	68
4.4.2 Discussion	70
CHAPTER5 CONCLUSIONS AND RECOMMENDATION	NS71
5.1 Conclusions	71
5.2 RECOMMENDATIONS	72
REFERENCES	73
APPENDIX	
EXAMPLES OF THE CODE USED FOR DATA ANALYSIS, MODEL DE	EVELOPMENT
AND THEIR CORRESPONDING RESULTS	
5.2.1 Importing relevant packages and loading data	
5.2.2 Exploratory data analysis	102
5.2.3 Encoding categorical variables	107
5.2.4 Scaling features	
5.2.5 Data shuffling	
5.2.6 Dividing data into train/validation/test	
5.2.7 Saving data for modeling	
5.2.8 Importing data for building the model	109
5.2.9 Fitting neural network model	
5.2.10 Evaluating the model on test data	
5.2.11 Plotting R-squared	
5.2.12 Saving and loading the model	
5.2.13 Creating model function	
5.2.14 Model Demo for end user	113

List of Tables

TABLE 2.1. COMPARISON BETWEEN GASIFICATION, COMBUSTION AND PYROLYSIS
TABLE 2.2. COMPARISON BETWEEN FOUR DIFFERENT TYPES OF SYNTHETIC GAS
[28]
TABLE 2.3. THE MOST RECENT MODELS BASED ON ELEMENTAL AND PROXIMATE
ANALYSIS
TABLE 2.4. THE PREDICTION OF HEATING VALUE USING ANN MODELS
TABLE 2.5. PUBLISHED GASIFICATION MODELING USING ANN
TABLE 2.6. PUBLISHED PYROLYSIS MODELING USING ANN
TABLE 3.1. THE STATISTICS OF DATA USED FOR HHV PREDICTION41
TABLE 3.2. STRUCTURE OF HHV FIRST PREDICTION MODEL
TABLE 3.3. STRUCTURE OF HHV SECOND PREDICTION MODEL
TABLE 3.4. STRUCTURE OF HHV SECOND PREDICTION MODEL
TABLE 3.5. THE STATISTICS OF DATA USED FOR GASIFICATION MODELING45
TABLE 3.6. STRUCTURE OF GASIFICATION PREDICTION MODEL45
TABLE 3.7. OPTIMUM INPUT PARAMETERS AND CORRESPONDING PREDICTED
RESPONSE FOR GASIFICATION ANN MODEL46
TABLE 3.8. THE STATISTICS OF DATA USED FOR FAST PYROLYSIS MODELING47
TABLE 3.9. STRUCTURE OF FAST PYROLYSIS PREDICTION MODEL
TABLE 3.10. STRUCTURE OF FAST PYROLYSIS PREDICTION MODEL
TABLE 3.11. STRUCTURE OF FAST PYROLYSIS PREDICTION MODEL
TABLE 3.12. OPTIMUM INPUT PARAMETERS AND CORRESPONDING PREDICTED
RESPONSE FOR FAST PYROLYSIS ANN MODEL50
TABLE 3.13. OPTIMIZATION RESULTS IN TERMS OF YIELDS OF EACH COMPONENT50
TABLE 3.14. THE STATISTICS OF DATA USED FOR SLOW PYROLYSIS MODELING 51
TABLE 3.15. STRUCTURE OF SLOW PYROLYSIS PREDICTION MODEL
TABLE 3.16. OPTIMUM INPUT PARAMETERS AND CORRESPONDING PREDICTED
RESPONSE FOR SLOW PYROLYSIS ANN MODEL
TABLE 4.1. REGRESSION STATISTICS FOR HHV FIRST ANN MODEL
TABLE 4.2. REGRESSION STATISTICS FOR HHV SECOND ANN MODEL56
TABLE 4.3. REGRESSION STATISTICS FOR HHV ANN MODEL
TABLE 4.4. REGRESSION STATISTICS FOR GASIFICATION ANN MODEL
TABLE 4.5. REGRESSION STATISTICS FOR FAST PYROLYSIS BIO-OIL ANN MODEL. 62

TABLE 4.6. REGRESSION STATISTICS FOR FAST PYROLYSIS BIO-GAS ANN MODEL 64 $^\circ$
TABLE 4.7. REGRESSION STATISTICS FOR FAST PYROLYSIS BIO-CHAR ANN MODEL 6
TABLE 4.8. REGRESSION STATISTICS FOR SLOW PYROLYSIS ANN MODEL

List of Figures

FIGURE 2.1. FIXED BED CO-CURRENT REACTOR
FIGURE 2.2. FLUIDIZED BED REACTOR
FIGURE 2.3. ENTRAINED FLOW REACTOR
FIGURE 2.4. CONFIGURATION OF THE UPDRAFT (COUNTER-CURRENT) GASIFIER 15 $$
FIGURE 2.5. DOWNDRAFT CO-CURRENT GASIFIER
FIGURE 2.6. CROSS FLOW GASIFIER
FIGURE 2.7. OPEN CORE GASIFIER
FIGURE 2.8. FLUIDIZED BED GASIFIER
FIGURE 2.9. THE ENTRAINED FLOW GASIFIER CONFIGURATION
FIGURE 2.10. TWO-STAGE BIOMASS GASIFIER OPTIMIZED FOR TAR ELIMINATION 20
FIGURE 2.11. MACHINE LEARNING: A NEW PROGRAMMING PARADIGM21
FIGURE 2.12. A SIMPLE NEURAL NETWORK (MINIMAL EXAMPLE)
FIGURE 2.13. NEURAL NETWORKS
FIGURE 2.14. ARCHITECTURE OF NEURAL NETWORKS
FIGURE 2.15. MODEL PARAMETER STRUCTURE
FIGURE 2.16. COMMON ACTIVATION FUNCTIONS
FIGURE 2.17. FORWARD PROPAGATION
FIGURE 2.18. BACKPROPAGATION
FIGURE 2.19. WEIGHT UPDATING MECHANISM
FIGURE 3.1. MACHINE LEARNING ALGORITHM COMPONENTS
FIGURE 3.2. OPTIMIZATION USING DIFFERENT GRADIENT-BASED OPTIMIZERS 40
FIGURE 3.3. ILLUSTRATION OF FLUIDIZED BED GASIFIER
FIGURE 4.1. ANN ARCHITECTURE OF HHV FIRST MODEL
FIGURE 4.2. THE REGRESSION PLOT OF TRAINING AND TESTING FOR HHV ANN
MODEL 54
FIGURE 4.3. RELATIVE SIGNIFICANCE OF INPUT VARIABLES FOR THE HHV55
FIGURE 4.4. ANN ARCHITECTURE OF HHV SECOND MODEL
FIGURE 4.5. THE REGRESSION PLOT OF TRAINING AND TESTING FOR HHV SECOND
ANN MODEL56
FIGURE 4.6. ANN ARCHITECTURE OF HHV THIRD MODEL57
FIGURE 4.7. THE REGRESSION PLOT OF TRAINING AND TESTING FOR HHV THIRD
ANN MODEL

FIGURE 4.8. ANN ARCHITECTURE OF GASIFICATION MODEL59
FIGURE 4.9. THE REGRESSION PLOT OF TRAINING AND TESTING FOR
GASIFICATION ANN MODEL59
FIGURE 4.10. RELATIVE SIGNIFICANCE OF INPUT VARIABLES FOR THE LHV 60
FIGURE 4.11. ANN ARCHITECTURE OF FAST PYROLYSIS BIO-OIL MODEL61
FIGURE 4.12. THE REGRESSION PLOT OF TRAINING AND TESTING FOR FAST
PYROLYSIS BIO-OIL ANN MODEL
FIGURE 4.13. RELATIVE SIGNIFICANCE OF INPUT VARIABLES FOR THE BIO-OIL
YIELD63
FIGURE 4.14. ANN ARCHITECTURE OF FAST PYROLYSIS BIO-GAS MODEL63
FIGURE 4.15. THE REGRESSION PLOT OF TRAINING AND TESTING FOR FAST
PYROLYSIS BIO-GAS ANN MODEL64
FIGURE 4.16. RELATIVE SIGNIFICANCE OF INPUT VARIABLES FOR THE BIO-GAS
YIELD65
FIGURE 4.17. ANN ARCHITECTURE OF FAST PYROLYSIS BIO-CHAR MODEL65
FIGURE 4.18. THE REGRESSION PLOT OF TRAINING AND TESTING FOR FAST
PYROLYSIS BIO-CHAR ANN MODEL
FIGURE 4.19. RELATIVE SIGNIFICANCE OF INPUT VARIABLES FOR THE BIO-CHAR
YIELD67
FIGURE 4.20. ANN ARCHITECTURE OF SLOW PYROLYSIS MODEL
FIGURE 4.21. THE REGRESSION PLOT OF TRAINING AND TESTING FOR SLOW
PYROLYSIS ANN MODEL69
FIGURE 4.22. RELATIVE SIGNIFICANCE OF INPUT VARIABLES FOR THE BIO-CHAR
YIELD

Nomenclature

AI Artificial Intelligence ANN Artificial neural network

C Carbon

ER Equivalence ratio FC Fixed carbon H Hydrogen

HHV Higher heating value

HR Heating rate

MSW Municipal solid waste

N NitrogenO OxygenPS Particle sizeS Sulfur

T Temperature VM Volatile matter