Deep Learning integrated with modelling a medical waste gasification-power production plant

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Approval Sheet

This thesis/dissertation/report entitled “Deep Learning integrated with modelling a medical waste gasification-power production plant” by Rahul N and Edla Sriharika is approved for the degree of Bachelor of Technology in Chemical Engineering.

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Certificate

It is certified that the work contained in the project titled, "Deep Learning integrated with modelling a medical waste gasification-power production plant" by Rahul N, and Edla Sriharika, bearing Roll Nos: 211817, 211805, respectively has been carried out under my supervision and that this work has not submitted elsewhere for a degree.

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Acknowledgements

To start off this acknowledgement, here is a quote that we hold close to our heart. "It's one small step, one giant leap!"

Subject to the limitations of time, efforts and resources, every possible attempt has been made to work on this project to identify and obtain fruitful results.

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Abstract

Medical Waste is any type of waste either solid or liquid comprising of harmful materials produced by healthcare facilities. It is trivially composed of biomass, and plastic waste in varying compositions. Improper handling of medical waste arises from the packing, segregation, treatment and disposal of medical waste. This is a serious issue due to its adverse effects on the enviromnent causing air, land and water pollution. To mitigate this issue, we have proposed a few methods to convert the medical waste into syngas using a technique called pyrolysis. A method called "plasma pyrolysis" has been explored in great detail. The generated syngas can then be combusted to generate power. We have focussed our work towards developing a Deep Learning model, that can learn from a dataset of simulations performed with different compositions of biomass, and can accurately predict the output power generated from a downdraft biomass gasification power production plant based on the composition of the biomass as its input parameters. The concepts of deep learning, neural network architecture, and optimization has been explored in great detail. Furthermore, we have also identified a few key areas in which development can be undertaken.

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1 Introduction

Medical waste (MW) consists of healthcare unit waste, medical laboratories waste, and biomedical research centres waste, and its inappropriate handling raises serious risks of disease transmission through exposure to infectious materials to the MW handlers, the health care personnel, the patients, and the public.

The need for MW management (MWM) has increased during the COVID-19 time mainly due to the increase in MW amount and because MW creates significant dangers for the environment and human health. The COVID-19 pandemic increased medical and municipal waste generation, in many countries by 350–500%, especially plastic waste in developing and developed countries, showing the greatest feature of final disposal in Finland with 75% recycling while lowest quality is in India where 90% is dumped.

Healthcare is a fast-developing industry due to the demand for more sophisticated/demanding medical treatments, resulting in an increasing need for MW treatment (MWT) and MW disposal (MWD). Since MW involves a significant quantity of hazardous substances, poor MWM might lead to serious environmental and human health risks. Life cycle assessment (LCA) and circular economy (CE) applied in the biomedical sector can deal with the medical, pharmaceutical, and dental wastes, describe the ways of MWM, face the problem of dental waste; and propose ways of 'green circulation' of this waste [4].

Thorough planning, usage of considerable mobile reprocessing facilities, and established procedures for discarding of MW could decrease the danger of COVID-19 spread in developing countries. Tirkolaee and Aydin [2] developed a sustainable MWM system for collection and transportation of MW in pandemics, they designed numerous various scales practical examples, solved the problem using CPLEX solver, and they compared diverse conditions. They also investigated the practical implications. Moreover, He et al. optimized the problem of the automated MW sorting system by taking into account the operational flow of MW [6]. They developed a mixed-integer programming model for the optimization of the MW assignment, presorting stations, and automated guided vehicles.

2 Theory and Literature Review

2.1 Causes of Medical Waste

Health-care waste contains potentially harmful microorganisms that can infect hospital patients, health workers and the general public. Other potential hazards may include drug-resistant microorganisms which spread from health facilities into the environment. Adverse health outcomes associated with health care waste and by-products also include:

- Sharps-inflicted injuries: Worldwide, an estimated 16 billion injections are administered every year. Not all needles and syringes are disposed of safely, creating a risk of injury and infection and opportunities for reuse. Injections with contaminated needles and syringes in low- and middle-income countries have reduced substantially in recent years, partly due to efforts to reduce reuse of injection devices. Despite this progress, in 2010, unsafe injections were still responsible for as many as 33,800 new HIV infections, 1.7 million hepatitis B infections and 315,000 hepatitis C infections. A person who experiences one needle stick injury from a needle used on an infected source patient has risks of 30%, 1.8%, and 0.3% respectively of becoming infected with HBV, HCV and HIV. Additional hazards occur from scavenging at waste disposal sites and during the handling and manual sorting of hazardous waste from health-care facilities. These practices are common in many regions of the world, especially in low- and middle-income countries. The waste handlers are at immediate risk of needle-stick injuries and exposure to toxic or infectious materials. In 2015, a joint WHO/UNICEF assessment found that just over half (58%) of sampled facilities from 24 countries had adequate systems in place for the safe disposal of health care waste.

- Toxic exposure to pharmaceutical products, in particular, antibiotics and cytotoxic drugs released into the surrounding environment, and to substances such as mercury or dioxins, during the handling or incineration of health care wastes
- Chemical burns arising in the context of disinfection, sterilization or waste treatment activities.
- Air pollution arising as a result of the release of particulate matter during medical waste incineration; thermal injuries occurring in conjunction with open burning and the operation of medical waste incinerators; and radiation burns.

2.2 Environmental Impact of Medical Waste disposal

Treatment and disposal of healthcare waste may pose health risks indirectly through the release of pathogens and toxic pollutants into the environment. The disposal of untreated health care wastes in landfills can lead to the contamination of drinking, surface, and ground waters if those landfills are not properly constructed. The treatment of health care wastes with chemical disinfectants can result in the release of chemical substances into the environment if those substances are not handled, stored and disposed in an environmentally sound manner.

Incineration of waste has been widely practised, but inadequate incineration or the incineration of unsuitable materials results in the release of pollutants into the air and in the generation of ash residue. Incinerated materials containing or treated with chlorine can generate dioxins and furans, which are human carcinogens and have been associated with a range of adverse health effects. Incineration of heavy metals or materials with high metal content (in particular lead, mercury and cadmium) can lead to the spread of toxic metals in the environment. Only modern incinerators operating at 850-1100 °C and fitted with special gas-cleaning equipment are able to comply with the international emission standards for dioxins and furans.

Alternatives to incineration such as autoclaving, microwaving, steam treatment integrated with internal mixing, which minimize the formation and release of chemicals or hazardous emissions should be given consideration in settings where there are sufficient resources to operate and maintain such systems and dispose of the treated waste.

2.3 Medical Waste Classification

Waste and by-products cover a diverse range of materials, as the following list illustrates:

Classification of Medical Waste	
Medical Waste Type	**Medical Waste Source**
Infectious waste	Waste contaminated with blood and other bodily fluids (e.g., from discarded diagnostic samples), cultures and stocks of infectious agents from laboratory work (e.g., waste from autopsies and infected animals from laboratories), or waste from patients with infections (e.g., swabs, bandages and disposable medical devices)
Pathological waste	Human tissues, organs or fluids, body parts and contaminated animal carcasses
Sharps Waste	Syringes, needles, disposable scalpels and blades, etc
Chemical waste	Solvents and reagents used for laboratory preparations, disinfectants, sterliants and heavy metals contained in medical devices (e.g., mercury in broken thermometers) and batteries
Pharmaceutical waste	Expired, unused and contaminated drugs and vaccines
Cytotoxic waste	Waste containing substances with genotoxic properties (i.e., highly hazardous substances that are, mutagenic, teratogenic or carcinogenic), such as cytotoxic drugs used in cancer treatment and their metabolites
Radioactive waste	Products contaminated by radionuclides including radioactive diagnostic material or radiotherapeutic materials
Non-hazardous or general waste	Waste that does not pose any particular biological, chemical, radioactive or physical hazard.

The major sources of health-care waste are:

- Hospitals and other health facilities.
- Laboratories and research centres.
- Mortuary and Autopsy centres.
- Animal research and testing laboratories.
- Blood banks and collection services.
- Nursing homes for the elderly.

High-income countries generate on average up to 0.5 kg of hazardous waste per hospital bed per day; while low-income countries generate on average 0.2 kg. However, health-care waste is often not separated into hazardous or non-hazardous wastes in low-income countries making the real quantity of hazardous waste much higher.

In a study published by Chih-Shan Li and Fu-Tien Jenq [9], the physical and elemental composition of the hospital waste at the National Taiwan University Hospital (NTUH), he estimated daily waste generation rate at NTUH was 4,600 kg/day, which consisted of 4,100 kg/day noninfectious refuse, 340 kg/day infectious waste, 70 kg/day kitchen waste, 50 kg/day pathological waste, and 40 kg/day plastic syringes. The NTUH waste consisted of 99.02% combustible wastes and 0.97% noncombustible wastes by mass. The combustibie wastes constituted paper (16.17%), textiles (9.77%), cardboard, wood, and leaves 1.12%), food waste (21.51%), and plastics (50.45%). The noncombustible waste included 0.40% metal and 0.57% glass. Furthermore, the analysis indicated that the wastes contained 38% moisture, 4% ashes, and 58% solid with an average heat value of 3,400 kcal/kg. From the elemental analysis, the dominant elements were found to be carbon (34%) and oxygen (15%).

2.4 Segregation of Medical Waste

Segregation refers to the basic separation of different categories of waste generated at source and thereby reducing the risks as well as cost of handling and disposal. Segregation is the most crucial step in bio-medical waste management. Effective segregation alone can ensure effective biomedical waste management.

Segregation reduces the amount of waste needs special handling and treatment. Effective segregation process prevents the mixture of medical waste like sharps with the general municipal waste and prevents the illegal reuse of certain components of medical waste like used syringes, needles and other plastics. It provides an opportunity for recycling certain components of medical waste like plastics after proper and thorough disinfection. Recycled plastic material can be used for non-food grade applications. Of the general waste, the biodegradable waste can be composted within the hospital premises and can be used for gardening purposes. Recycling is a good environmental practice, which can also double as a revenue generating activity. It also reduces the cost of treatment and disposal (80 per cent of a hospital's waste is general waste, which does not require special treatment, provided it is not contaminated with other infectious waste).

COLOUR CODING FOR SEGREGATION OF BIOMEDICAL WASTE

CATEGORY	TYPE OF WASTE	TYPE OF BAG OR CONTAINER TO BE USED	TREATMENT AND DISPOSAL OPTION
Yellow	Human tissues, organs, body parts	Yellow coloured non chlorinated plastic bags	Incineration or deep burial
Red	Contaminated waste (Recyclable)	Red coloured non-chlorinated plastic bags or containers	Autoclaving or microwaving or chemical treatment
Black	Discarded medicines/cytotoxic drugs, incineration ash, chemical waste	Black coloured non-chlorinated plastic bags	Disposal in secured landfill
Blue/white	Waste sharps(needles, scalpels, blades)	Cardboard boxes with blue colored marking	Autoclaving or microwaving or chemical treatment & destruction

Figure 1: Colour Coding for the segregation of Medical Waste

2.5 Steps in the management of Medical Waste

We now come to one of the most important segments that has to be dealt with when handling medical waste. Some of the steps to ensure proper management of Medical Waste are as follows:

1. **Proper labelling of bins:** The bins and bags should carry the biohazard symbol indicating the nature of waste to the patients and public.

2. **Collection:** The collection of biomedical waste involves use of different types of container from various sources of biomedical wastes like Operation Theatre, laboratory, wards, kitchen, corridor etc. The containers/ bins should be placed in such a way that 100% collection is achieved. Sharps must always be kept in puncture-proof containers to avoid injuries and infection to the workers handling them.

3. **Storage:** Once collection occurs then biomedical waste is stored in a proper place. Segregated wastes of different categories need to be collected in identifiable containers. The duration of storage should not exceed for 8-10 hrs in big hospitals (more than 250 bedded) and 24 hrs in nursing homes. Each container may be clearly labelled to show the ward or room where it is kept. The reason for this labelling is that it may be necessary to trace the waste back to its source. Besides this, storage area should be marked with a caution sign.

4. **Transportation:** The waste should be transported for treatment either in trolleys or in covered wheelbarrow. Manual loading should be avoided as far as for as possible. The bags / Container containing BMWs should be tied/lidded before transportation. Before transporting the bag containing BMWs, it should be accompanied with a signed document by Nurse/Doctor mentioning date, shift, quantity and destination. Special vehicles must be used so as to prevent access to, and direct contact with, the waste by the transportation operators, the scavengers and the public. The transport containers should be properly enclosed. The effects of traffic accidents should be considered in the design, and the driver must be trained in the procedures he must follow in case of an accidental spillage. It should also be possible to wash the interior of the containers thoroughly.

5. **Personnel safety devices:** The use of protective gears should be made mandatory for all the personnel handling waste.

    - Gloves: Heavy-duty rubber gloves should be used for waste handling by the waste retrievers. This should be bright yellow in colour. After handling the waste, the gloves should be washed twice. The gloves should be washed after every use with carbolic soap and a disinfectant. The size should fit the operator.
    - Aprons, gowns, suits or other apparels: Apparel is worn to prevent contamination of clothing and protect skin. It could be made of cloth or impermeable material such as plastic. People working in incinerator chambers should have gowns or suits made of non-inflammable material.
    - Masks: Various types of masks, goggles, and face shields are worn alone or in combination, to provide a protective barrier. It is mandatory for personnel working in the incinerator chamber to wear a mask covering both nose and mouth, preferably a gas mask with filters.
    - Boots: Leg coverings, boots or shoe-covers provide greater protection to the skin when splashes or large quantities of infected waste have to be handled. The boots should be rubber-soled and anti-skid type. They should cover the leg up to the ankle.

6. **Cleaning devices:**

    - Brooms: The broom shall be a minimum of 1.2 m long, such that the worker need not stoop to sweep. The diameter of the broom should be convenient to handle. The brush of the broom shall be soft or hard depending on the type of flooring.
    - Dustpans: The dustpans should be used to collect the dust from the sweeping operations. They may be either of plastic or enamelled metal. They should be free of ribs and should have smooth contours, to prevent dust from sticking to the surface. They should be washed with disinfectants and dried before every use.
    - Mops: Mops with long handles must be used for swabbing the floor. They shall be of either the cloth or the rubber variety. The mop has to be replaced depending on the wear and tear. The mechanical-screw type of mop is convenient for squeezing out the water.

- Vacuum cleaners: Domestic vacuum cleaners or industrial vacuum cleaners can be used depending on the size of the rooms.

7. **Storage devices**

   - Dustbins: It is very important to assess the quantity of waste generated at each point. Dustbins should be of such capacity that they do not overflow between each cycle of waste collection. Dustbins should be cleaned after every cycle of clearance of waste with disinfectants. Dustbins can be lined with plastic bags, which are chlorine-free, and colour coded as per the law.

8. **Handling devices**

   - Trolleys: The use of trolleys will facilitate the removal of infectious waste at the source itself, instead of adding a new category of waste.
   - Wheelbarrows: Used to transfer the waste from the point source to the collection centres. There are two types of wheelbarrow – covered and open. Wheelbarrows are made of steel and provided with two wheels and a handle. Care should be taken not to directly dump waste into it. Only packed waste (in plastic bags) should be carried. Care should also be taken not to allow liquid waste from spilling into the wheelbarrow, as it will corrode. These are ideal for transferring debris within the institution. Wheelbarrows also come in various sizes depending on the utility.
   - Chutes: Chutes are vertical conduits provided for easy transportation of refuse vertically in case of institutions with more than two floors. Chutes should be fabricated from stainless steel. It should have a self-closing lid. These chutes should be fumigated everyday with formaldehyde vapours. The contaminated linen (contaminated with blood and or other body fluids) from each floor should be bundled in soiled linen or in plastic bags before ejecting into the chute. Alternately, elevators with mechanical winches or electrical winches can be provided to bring down waste containers from each floor. Chutes are necessary to avoid horizontal transport of waste thereby minimizing the routing of the waste within the premises and hence reducing the risk of secondary contamination

2.6 Plasma Pyrolysis of Medical Waste

Plasma is the state of matter obtained by breaking down atoms into ions and electrons by the process of ionization. Plasmas can quite easily reach temperatures of 10,000 degree Celcius. Plasma technologies offer unique solutions to meet the increasing demands of dematerialization to develop ecologically sensible industrial practices like high temperatures, high chemical reactivity, high energy density and ability to process solids, liquids and gases. In plasma pyrolysis, generation of heat is independent of chemistry of material used. It is fast heating – 5000 °C can be achieved in milliseconds. It is fast quenching and consumes small quantity of gas. The high ultraviolet radiation flux destroys pathogens and waste to be treated, could be dry or wet. It is possible to recover energy in the form of carbon monoxide and hydrogen.

The Facilitation Centre for Industrial Plasma Technologies (FCIPT) of the Institute of Plasma Research, Gandhinagar, Gujarat, an aided institute of DAE, has developed Pyrolysis System using plasma for disposal of medical waste [10].

Technical Brief of Plasma Pyrolyser: Plasma Pyrolysis System incorporates "CASS" (Complete Automated Safety System) that ensures an operating environment, which exceeds any safety norms. The cost of installing, operating and maintaining the Plasma Pyrolysis System is on par with conventional incineration facilities of similar capacity. The inherent simplicity, lack of moving parts, system redundancy, automation, and proven stability of the Plasma Pyrolysis System ensure very high reliability with minimal downtime and maintenance requirements. Electricity requirement is very low. It is less than 1 kWh per kg of charge (approx.). With the exception of start up and shut down, the plasma field is normally sufficient to maintain operating temperatures. With the additions of oxygen generators and co-generation, operating cost are well below and conventional waste processing or energy production systems in the market today.

The **Bio-Medical Waste Disposal System** is under actual field trials at the Gujarat Cancer Research Institute, Ahmedabad since August 2001. It has been operated for disposal of infected bio-medical waste including plastics, cotton, pathological waste and tissues. The waste is treated for disposal as collected from the hospital without any segregation or pre-treatment. The system was run on a continuous basis for 4 to 5 hours per day. The rate of disposal was 18 - 20 kg/h. In December 2001, the system was tested for more than 100 hours for various combinations of waste material and operating conditions. More than 500 kg. of infected bio-medical waste was treated. The system was run exclusively for treated human tissues and pathological waste. During trials 100 kg of tissues were treated. The System is microprocessor controlled, allowing one individual to operate one processing reactor systems, including loading and temperature controls.

Plasma torch: The plasma torch consists of a water-cooled tungsten tip with an auxiliary copper anode surrounding it. The water-cooled anode cup is placed in front of the cathode. Both anode and cathode are surrounded by a magnetic field coil, which produces an axial magnetic field parallel to both the anode and cathode axes. The whole torch assembly is mounted on a flange of 100 mm diameter in a side port. The arc is initiated between the cathode and the auxiliary anode, and then transferred to the copper anode. The spectroscopic measurement suggests that the temperature near the cathode is around 20,000 K, while near the anode tip it is around 7000 K. The temperature is around 1500 K close to the waste. In addition, the hot flame rises and spreads out. The plasma-arc jet is shown in Figure 2.

Power supply: Fifty kW DC power supply used for plasma pyrolysis experiments has been developed indigenously. This power supply has open circuit voltage of 400 V, arc voltage of 125 V and maximum arc current of 400 amperes. It has a high voltage (3.5 kV) and high frequency (4 MHz) arrangement to strike the arc.

Figure 2: Plasma Torch producting high temperature plasma

Gas-injection system: N_2 gas is injected through the torch and flow of gas is controlled using rotameters. There is an arrangement in the torch port to introduce steam or compressed air in the reaction zone of the primary chamber.

Process chamber: The process chamber is inclined as shown in Figure. It is made up of mild steel and has waste-feeding arrangement, mild-steel shell, glass-wool shielding, etc. The feeder has a double-door facility, where the inner door has a fish-mouth locking which avoids leakage of the gas. The door operates pneumatically. The outer door of the feeder has proper sealing to prevent gases from spreading in the working environment, while the inner door is opened for feeding the material.

Secondary chamber: While disposing contaminated hospital waste, one important requirement is that the gases, which come out from the primary chamber, have to pass through a temperature zone of 1050 ± 50 °C in the secondary chamber. Hot gases produced in the primary chamber contain hydrocarbons, carbon monoxide and hydrogen in excess quantity. These gases are burnt in the secondary chamber with some excess quantity of air and they convert into CO2 and H2O. The secondary chamber is designed in such a way that the residence time of the gases is sufficient for combustion reactions to be completed.

The quenching-cum-scrubbing system: The quenching-cum-scrubbing system is made up of mild steel and has ceramic lining at the inner wall of the chamber. NaOH solution pH 12, at normal temperature is circulated with the help of a fountain in the chamber. Hot gases that pass through the scrubber are quenched to inhibit recombination reactions. The height of the scrubber is selected in such a way so that it maintains sufficient residence of the gases to reduce the temperature from 1000 °C to ambient. Use of dilute NaOH will remove HCl from the residual gases. Induced draft fan and chimney Induced draft fan is used to take the residual gases at the chimney's height where these gases are released in the atmosphere, The fan also serves to create negative pressure in the primary chamber and to suck excess air in to the secondary chamber for combustion reactions.

Description of pyrolysis process: An arc is produced between the two electrodes using dc power supply. A high voltage, high frequency generator is used to strike the plasma. The magnetic field rotates the arc root at the anode to reduce electrode wear. N_2 gas is employed to produce plasma. The required process temperature, approximately 900 °C in the primary chamber, is attained rapidly. The pyrolyzed gases are burned in the presence of excess air in the secondary chamber. Combustion of the pyrolyzed gases takes place and a long flame is observed, The gas samples are collected at the outlet of the secondary chamber for analysis. After combustion, the hot gases are passed through a quencher-cum-scrubber, where the gases are quenched in alkaline water (12 pH) which brings down their temperature to 80 °C or less. In case chlorinated waste is pyrolysed, HCl is one of the gaseous components produced that is scrubbed-off by the alkaline solution. The quenching restricts recombination reactions which otherwise produce toxic compounds. The residual gases are released with the help of an induced draft fan and chimney. Destruction of Bacillus stearothermophilus and Bacillus subtilis bacteria grown on stainless-steel strips and exposed to the plasma environment in the primary chamber, has been demonstrated [11].

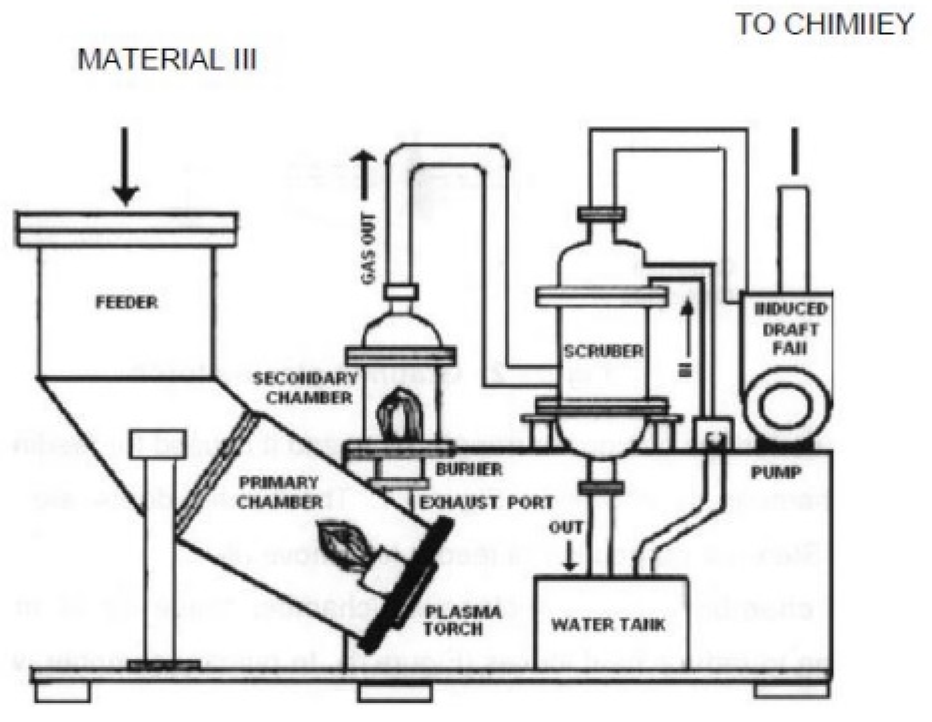

Figure 3: Plasma Pyrolysis setup

2.7 Syngas production and combustion

We have seen that the plasma gasification is a good alternative for processing biomedical waste. The syngas produced has a medium potential for electricity generation. In the best scenario, the payback is 6 years, although the technology is expensive.

Brazil has problems with the incorrect disposal of biomedical waste (BW) and studies of new technologies to eliminate this problem is becoming increasingly important. The plasma gasification technology provides reliable destruction of polluting materials, produces an inert slag and syngas. The slag can be used in civil construction, whereas syngas can be burned in the internal combustion engine (ICE) for electricity and heat generation. To collaborate with the insertion of plasma gasification technology in the Brazilian scenario, thermodynamic and economic studies of the use of BW plasma gasification are developed in this work and applied to conditions of Guaratinguetá city, São Paulo state, Brazil. Initially, the thermodynamic analysis was performed to determine the energetic efficiency of the plasma gasification system coupled with the ICE and the electricity generation potential was determinate. Economic studies were conducted to determine syngas and electricity production cost, the payback period and expected annual saving of the system. Thermodynamic analysis showed that the energy efficiency of the plasma gasifier is 78.58% and that there is a potential to produce 31% of the electricity required in the BW plasma gasification system. Through economic analysis the payback obtained was 6 years.

Despite its drawbacks, this process is being studied. Due to its high temperature, during the processing of plastics by plasma pyrolysis, energy from these materials is mainly recovered in the form of synthesis gas. This gas can be used to generate the necessary electricity to power plasma devices, which reduces its consumption. The synthesis gas mainly consists of carbon monoxide and hydrogen and may be used for fuel production (such as methanol, diesel oil) or hydrogen extraction.

The clean exhaust steam released in the process is known as syngas which can further be used indigenously to produce electricity and other fermentation purposes. The generation of electricity from the syngas can able to reproduce the electricity up to 31% of that used for the plasma pyrolysis operation. The exact thermodynamics of the pyrolysed gas must be evaluated for the regeneration of electricity [13].

The reactions involved in the pyrolysis which leads to syngas production and combustion processes are:

$$\begin{aligned}
\mathrm{C_6H_{10}O_5(cellulose) + heat} &\longrightarrow \mathrm{CH_4 + 2\ CO + 3\ H_2O + 3\ C} \\
[-\mathrm{CH_2 - CH_2}-]_n\ \mathrm{(polyethylene) + H_2O + heat} &\longrightarrow \mathrm{xCH_4 + yH_2 + zCO} \\
\mathrm{CO} + \frac{1}{2}\mathrm{O_2} &\longrightarrow \mathrm{CO_2} \qquad \Delta\mathrm{H} = -67.63\ \mathrm{kcal} \\
\mathrm{H_2} + \frac{1}{2}\mathrm{O_2} &\longrightarrow \mathrm{H_2}O \qquad \Delta\mathrm{H} = -57.82\ \mathrm{kcal}
\end{aligned}$$

We find that upon combustion of a 1:1 mixture of Syngas (CO + H_2), an exothermic reaction occurs with the release of $\Delta H = -125.45$ kcal

2.8 Preliminary plant design

We have used the software **Aspen Plus v11** to design the plant which produces syngas. The design of this plant is illustrated in the image below.

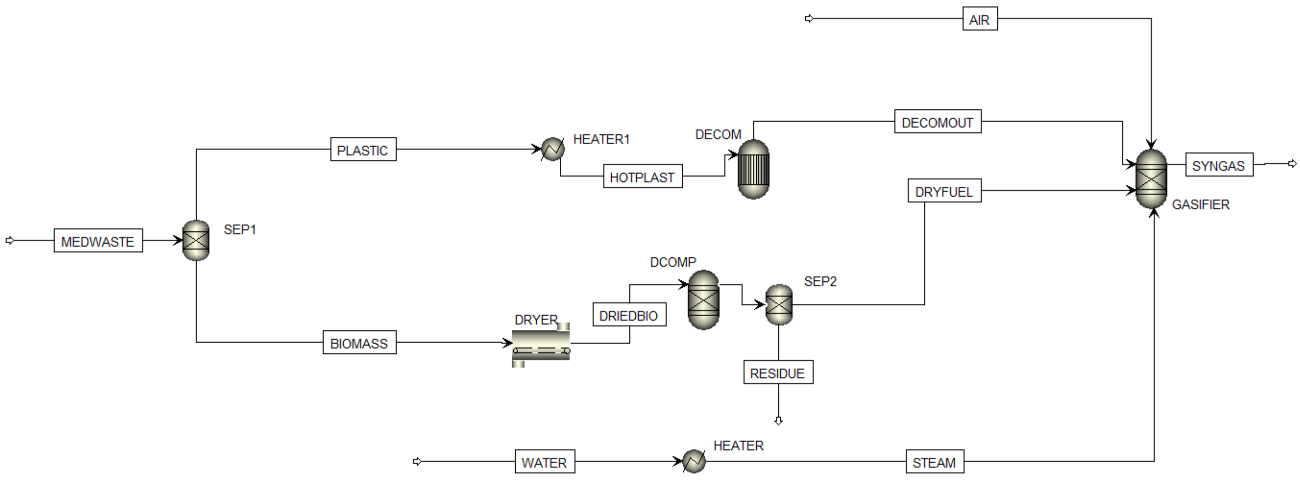

Figure 4: Preliminary Plant Design

Medical Waste is first separated into biomass and plastic, after which the biomass undergoes drying and the plastic is heated before being sent to the pyrolysis unit. The dried biomass is also pyrolysed, and the gases are sent to the Gasifier. The Gasifier takes in a mixture of air and steam, and produces syngas ($CO + H_2$)

Inorder to extract energy from the produced syngas, we make use of the design as suggested by Safarian et.al., [15]. The design is illustrated below.

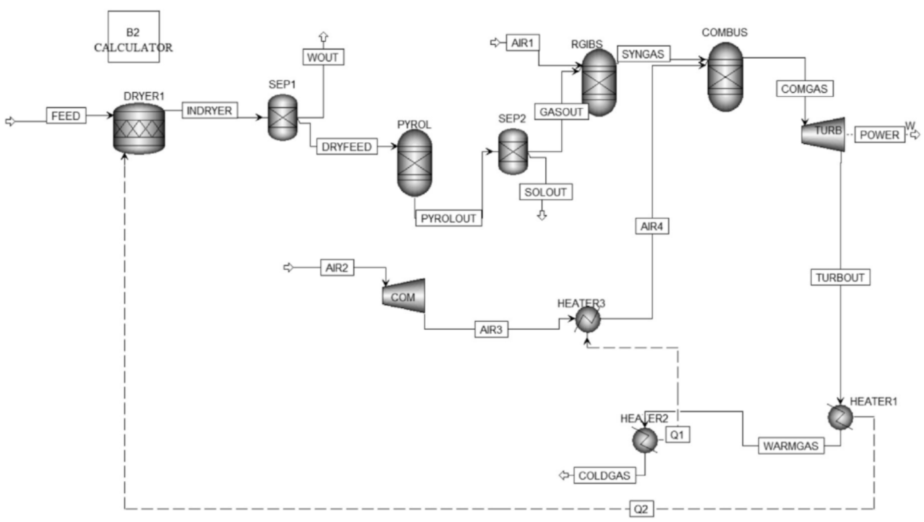

Figure 5: Plant Design to extract power

The gasifier used here is a downdraft gasifier. After production of the syngas in the block named **SYNGAS**, the gas is then sent to be combusted along with a mixture of heated air. The heat produce from the exothermic reaction is used to drive a turbine, that generates power. In this work done by Safarian et.al., Penge Robinson equation of state with Boston-Mathias alpha function (PR-BM) is applied to calculate physical properties of the conventional components in the gasification process. HCOALGEN and DCOALIGT models are also employed for enthalpy and density of biomass and ash which are non-conventional components. The factors that affect how much power can be generated are Moisture Content (wt%), Volatile Materials (wt% dry basis), Fixed Carbon (wt% dry basis), ash (wt% dry basis), Carbon (wt% dry basis), Oxygen (wt% dry basis), Hydrogen(wt% dry basis), Nitrogen (wt% dry basis), Sulphur (wt% dry basis), gasifier temperature, Gasifier Temperature (°C) and air to fuel ratio (kgair/kgdrybiomass). These properties are derived from the Proximate and Elemental analysis of a variety of biomass types such as Alder-fir sawdust, Balsam bark, Birch bark, e.t.c.

2.9 Neural Networks

Artificial neural networks (ANN) have been developed as generalizations of mathematical models of biological nervous systems. The advantage of the brain is its effective use of massive parallelism, the highly parallel computing structure, and the imprecise information-processing capability [1].

Artificial neural networks have been applied to problems ranging from speech recognition to prediction of protein secondary structure, classification of cancers and gene prediction. In 1943, McCulloch and Pitts modeled a neuron as a switch that receives input from other neurons and, depending on the total weighted input, is either activated or remains inactive. The weight, by which an input from another cell is multiplied, corresponds to the strength of a synapse—the neural contacts between nerve cells. These weights can be both positive (excitatory) and negative (inhibitory) [8]. For instance for a given set of weights and biases, mathematically the output of a neuron can be expressed as

$$y_{in} = \sum_{i=1}^{n} w_i x_i + b \tag{1}$$

$$y = \begin{cases} 1, & \text{if } f(y_{in}) \geq \theta, \\ 0, & \text{if } f(y_{in}) < \theta, \end{cases} \tag{2}$$

where θ is the threshold value and f is the activation function.

The neural network (Fig. 1) can be trained on a set of examples using a special learning rule. The weights are changed in proportion to the difference (error) between the target output (t), and the network output (y), for each example. The error is a function of all the weights and forms an irregular multidimensional complex hyperplane with many peaks, saddle points, and minima. Using a specialized search technique, the learning process strives to obtain the set of weights that corresponds to the global minimum. Some of the most common problems that can be undertaken using ANNs are [3].

- **Pattern Classification:** Deals with assigning an unknow input pattern using supervised learning, to one of several specified classes based on one or more properties that

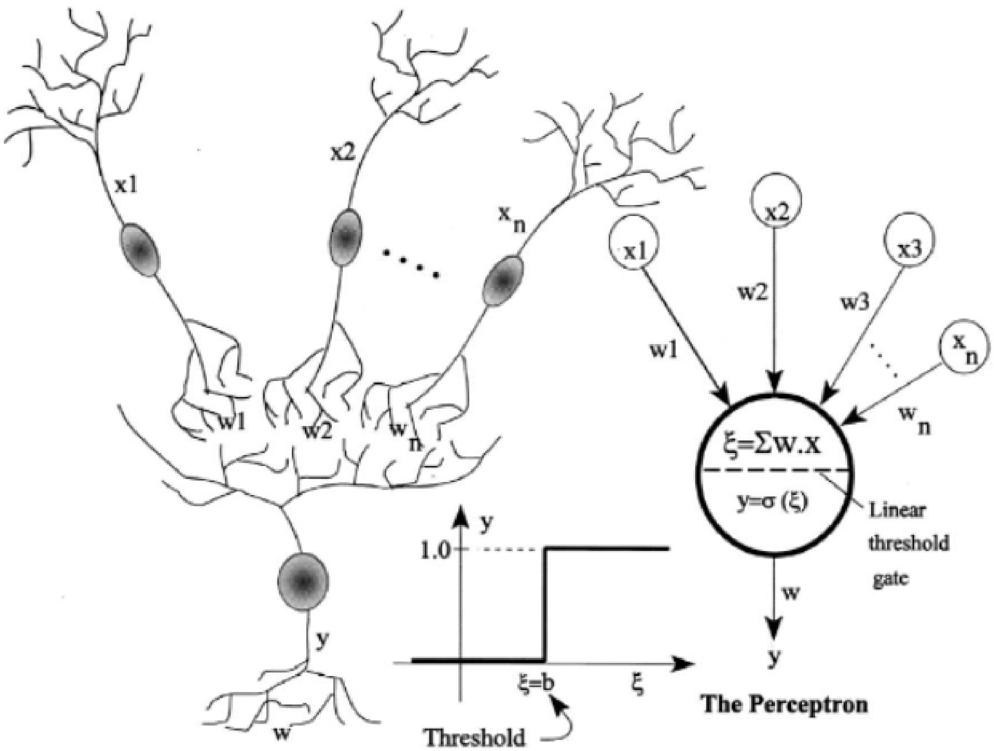

Figure 6: Analogy between a biological neuron and an artificial neuron.

characterize a given class.

- **Clustering:** Clustering is performed via unsupervised learning in which the clusters (classes) are formed by exploring the similarities or dissimilarities between the input patterns based on their inter-correlations. The network assigns 'similar' patterns to the same cluster.

- **Function Approximation:** Function approximation (modeling) involves training ANN on input–output data so as to approximate the underlying rules relating the inputs to the outputs. Multilayer ANNs are considered universal approximators that can approximate any arbitrary function to any degree of accuracy and thus are normally used in this application. Function approximation is applied to problems (i) where no theoretical model is available, i.e., data obtained from experiments or observations are utilized, or (ii) to substitute theoretical models that are hard to compute analytically by utilizing data obtained from such models.

- **Forecasting:** Forecasting includes training of an ANN on samples from a time series representing a certain phenomenon at a given scenario and then using it forother scenarios to predict (forecast) the behavior at ubsequent times. That is, the network will predict $Y(t+1)$ from one or more previously known historical observations [e.g., $Y(t-2)$, $Y(t-1)$, and $Y(t)$, where t is the time step].

In this work, we focus on using an ANN that carries out function approximation to predict the output power of a downdraft biomass gasifier plant, based upon 11 input parameters. The details are provided in the upcoming sections.

2.10 Activation Functions

The activation function is a non-linear transformation that we do over the input before sending it to the next layer of neurons or finalizing it as output [7]. The activation function plays a major role in the success of training deep neural networks. It manipulates the presented data through gradient descent and afterwards produce an output for the neural network, that contains the parameters in the data. These AFs are often referred to as a transfer function in some literature and help decide if a neuron should be fired or not. Many activation functions exist in literature. Some of them are discussed below [12].

- **Sigmoid Function:** This is referred to as logistic function or squashing function in some literature It is a bounded differentiable real function, defined for real input values, with positive derivatives everywhere given by,

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

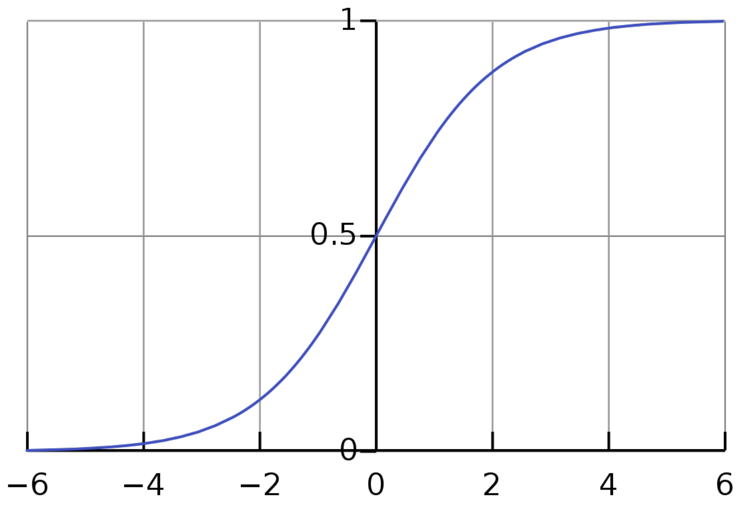

Figure 7: Sigmoid Activation Function

- **Hyperbolic Tangent Function:** The hyperbolic tangent function, also known as tanh function is a smoother, zero centered function whose range lies between -1 and 1. It is defined as,

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{4}$$

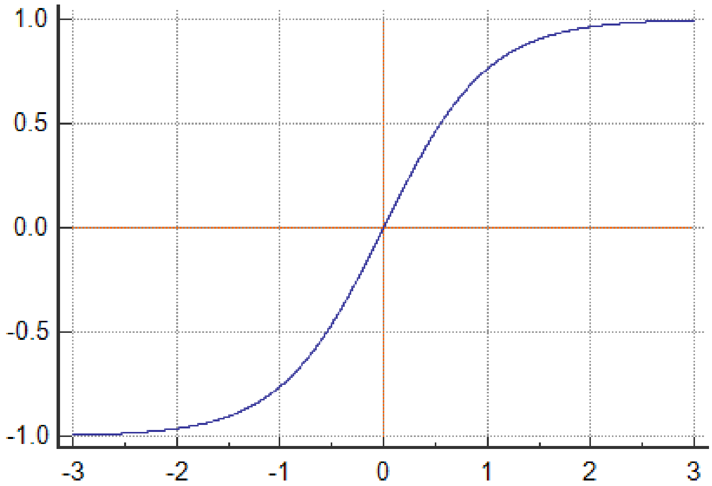

Figure 8: tanh Activation Function

- **Softmax Function:** The Softmax function is another types of activation function used in neural computing. It is used to compute probability distribution from a vector of real numbers. The Softmax function produces an output which is a range of values between 0 and 1, with the sum of the probabilities been equal to 1. It can be computed as

$$f(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}} \tag{5}$$

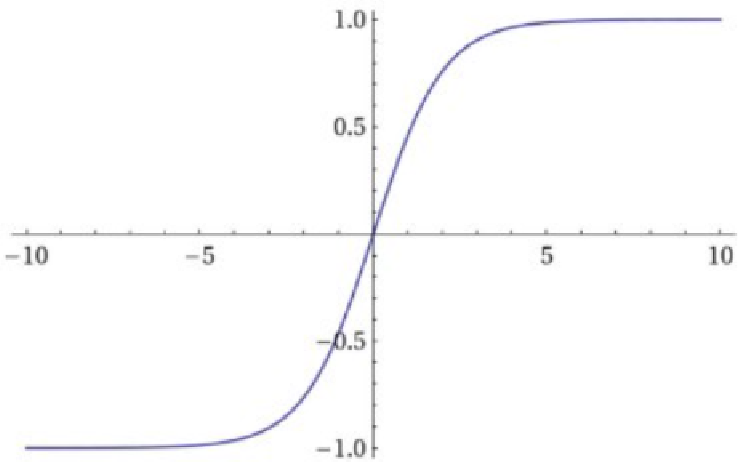

Figure 9: Softmax Activation Function

- **Rectified Linear Unit Function:** The ReLU is a faster learning AF, which has proved to be the most successful and widely used function. It offers the better performance and generalization in deep learning compared to the Sigmoid and tanh activation function. The ReLU activation function performs a threshold operation to each input element where values less than zero are set to zero thus the ReLU is given by

$$f(x) = max\{0, x\} = \begin{cases} x_i, & \text{if } x_i \geq 0 \\ 0, & \text{if } x_i < 0 \end{cases} \tag{6}$$

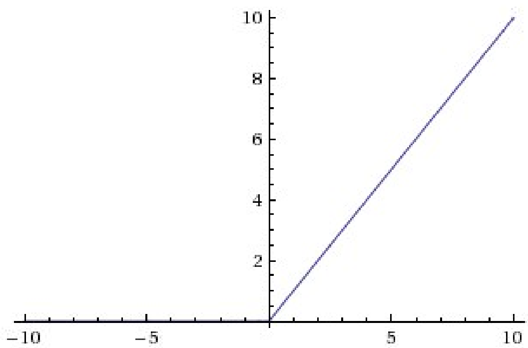

Figure 10: ReLU Activation Function

2.11 Optimization and Stochastic Gradient Descent

Optimization deals with the selection of a best element, with regard to some criterion, from some set of available alternatives. The standard form for a single-objective, non-linear, constrained optimization problem is given by [17]:

$$\begin{aligned} \text{Minimize:} \quad & f(\mathbf{x}) \\ \text{Subject to:} \quad & g_j(\mathbf{x}) \leq 0 \qquad j = 1, 2, \dots m \\ & h_k(\mathbf{x}) = 0 \qquad k = 1, 2, \dots p \\ & x_{iL} \leq x_i \leq x_{iU} \quad i = 1, 2, \dots n \end{aligned} \tag{7}$$

$f(\mathbf{x})$ is the objective function needed to be minimized.

We have 2 kinds of optimization algorithms

- Local Optimization Algorithms: This consists of optimizing a function at a locality. Some methods include:
    1. Gradient Based Algorithms: In this methods, the basic idea is to iteratively find the optimum using the equation

    $$x^q = x^{q-1} + \alpha S^q \tag{8}$$

    Where α is the step size taken to reach the new point x^q and S^q is the new search direction in which to move given by the direction opposite to increasing gradient.
    2. Newton's Method
    3. Unconstrained Optimization

4. Constrained Optimization
5. Non-Gradient Based Methods

- Global Optimization algorithms
  1. Evolutionary Algorithms
  2. Deterministic Algorithms

Stochastic Gradient Descent: The term "stochastic" means a mechanism or a method connected to a random possibility; therefore, instead of the entire data set for each iteration, a few samples are randomly chosen. In SGD, a hyperparameter termed "momentum" may also be introduced. Momentum is designed to learn quickly, especially in the face of wide curvatures, small yet noisy gradients, or stable gradients [5]. The usage of a momentum term is another approach that can assist the network to get rid of local minima. The momentum term increases for dimensions whose gradients point in the same directions and reduces updates fordimensions whose gradients change directions. As a result, we gain faster convergence and reduced oscillation [14].

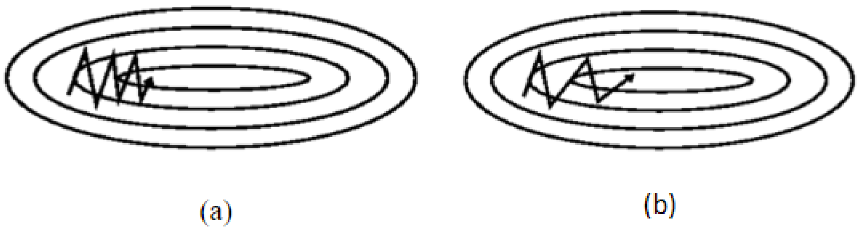

Figure 11: (a) SGD without Momentum (b) SGD with Momentum

$$
\begin{aligned}
(a) \quad & \theta = \theta - v_t, \text{ where} \\
& v_t = \gamma v_t + \eta \nabla_\theta J(\theta; x^i; y^i) \\
(b) \quad & \theta = \theta - \eta \nabla_\theta J(\theta; x^i; y^i)
\end{aligned} \tag{9}
$$

Adam Optimization: Adam is a method of SGD optimization that measures adaptable learning rates for each parameter. Adam is one of the most common step-size strategies in the field of neural networks. The name was taken from Adaptive Moments. Adam lowers computing costs, needs less execution memory. It is a combination of the following Algorithms

- Adaptive Gradient Algorithm (AdaGrad) that maintains a per-parameter learning rate that improves performance on problems with sparse gradients (e.g. natural language and computer vision problems).
- Root Mean Square Propagation (RMSProp) that also maintains per-parameter learning rates that are adapted based on the average of recent magnitudes of the gradients for the weight (e.g., how quickly it is changing). This means the algorithm does well on online and non-stationary problems (e.g., noisy) [14].

We can compute the Adam Optimization as follows. We calculate 2 parameters $\hat{m_t}$ and $\hat{v_t}$:

$$\begin{aligned} m_t &= \beta_1 m_{t-1} + (1-\beta_1)\left[\frac{\delta L}{\delta w_t}\right] \\ v_t &= \beta_2 v_{t-1} + (1-\beta_2)\left[\frac{\delta L}{\delta w_t}\right]^2 \\ \hat{m_t} &= \frac{m_t}{1-\beta_1^t}, \hat{v_t} = \frac{v_t}{1-\beta_2^t} \end{aligned} \tag{10}$$

Substituting these in the general equation given by (8), we get

$$x_{t+1} = x_t - \alpha\left(\frac{\hat{m_t}}{\sqrt{\hat{v_t}}+\epsilon}\right) \tag{11}$$

2.12 Pytorch Deep Learning Framework

PyTorch is an open-source library that can be used for free by everyone. It provides us with a scalable, multiplatform programming interface for implementing and running machine learning algorithms. Over the years, PyTorch has evolved into one of the two most popular frameworks for deep learning. It uses dynamic computational graphs, which have the advantage of being more flexible compared to its static counterparts. Dynamic computational graphs are debugging friendly: PyTorch allows for interleaving the graph declaration and graph evaluation steps. You can execute the code line by line while having full access to all variables. This is a very important feature that makes the development and training of NNs very convenient. Another key feature of PyTorch, is its ability to work with single or multiple graphical processing units (GPUs). This allows users to train deep learning models very efficiently on large datasets and large-scale systems. Last but not least, PyTorch supports mobile deployment, which also makes it a very suitable tool for production. PyTorch performs its computations based on a directed acyclic graph (DAG) [16].

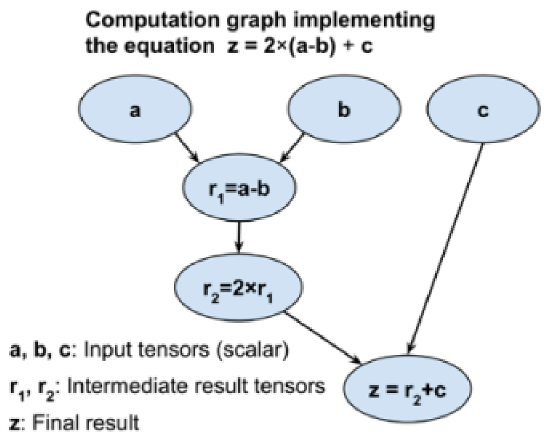

Figure 12: How a computational graph works?

2.13 Neural Network Architecture

In this work, we consider a fully connected neural network with 3 layers. The first layer is an input layer with 11 input neurons. These inputs are a vector of the values of Moisture Content (wt%), Volatile Materials (wt% dry basis), Fixed Carbon (wt% dry basis), ash (wt% dry basis), Carbon (wt% dry basis), Oxygen (wt% dry basis), Hydrogen(wt% dry basis), Nitrogen (wt% dry basis), Sulphur (wt% dry basis), gasifier temperature, Gasifier Temperature (°C) and air to fuel ratio (kgair/kgdrybiomass). The second layer is a hidden layer with 40 neurons as this structure minimizes the overall mean squared loss calculated. The third layer is the output layer, which has one output value. The sigmoid activation function is used in the hidden layer, given by the equation

$$f(x) = \frac{1}{1 + e^{-x}} \tag{12}$$

The neural network is constructed with the architecture as follows.

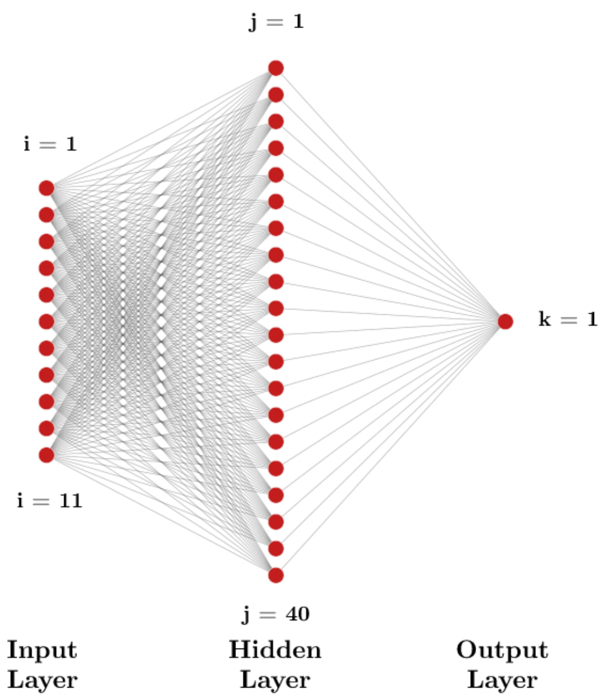

Figure 13: Neural Network Architecture

3 Code Snippets

This section details snippets of the code which was used to construct the artifical neural network. First, we make the necessary imports.

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader
from sklearn.model_selection import train_test_split
```

Listing 1: Making necessary imports

The **import torch** imports the **PyTorch** package, and its related modules. We utilize the **torch.nn**, **torch.optim**, **torch.utils.data** packages in this work. **torch.nn** is a package that contains basic building blocks for the computational graphs. **torch.optim** is a package for implementing various optimization algorithms. Data loading utility onto the constructed PyTorch Model is offered the **torch.utils.data.DataLoader** We also import the **train_test_split** from the **scikit-learn** package inorder to split our data into testing and training sets.

```
class NeuralNetwork(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(NeuralNetwork, self).__init__()
        self.firstlayer = nn.Linear(input_size, hidden_size)
        self.secondlayer = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        x = self.firstlayer(x)
        x = nn.Sigmoid()(x)
        x = self.secondlayer(x)
        return x

    def predict(self, x):
        pred = self.forward(x)
        return pred
```

Listing 2: Construction of the Network Class

Here, we create a python class named **NeuralNetwork** for our neural network by inheriting the parent class **nn.Module**. We create a constructor with 3 input parameters denoting the sizes of the nodes: **input_size**, **hidden_size**, and **output_size**. The constructor also initializes 2 values **self.firstlayer**, and **self.secondlayer** with the **nn.Linear** unit, each taking in the respective sizes of the input and output nodes. The Linear Unit is given by the following equation:

$$y = \mathrm{w}^T\mathbf{X} + b \tag{13}$$

where **X** is the vector of inputs, w is the weight vector, and b is the bias vector. Now, we create two functions name **forward** and **predict**. The **forward** function takes in the input vector **X** and does the forward propagation step of the neural network training. The output from the **self.firstlayer** is passed to the hidden layer. The activation function used in the hidden layer is given by **nn.Sigmoid()**, the output of which is passed to the **self.secondlayer**. The output is y is given from this second layer.

We now begin training the model using 10000 epochs. We specify a **learning rate** of 0.0002 to have a nice and steady learning process, and we consider the loss/cost function as **nn.MSELoss()**. The **nn.MSELoss()** is calculated as

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i^{pred} - y_i)^2 \tag{14}$$

We call **optim.Adam()** function to invoke the Adam Optimizer discussed in the previous sections to minimize the network parameters with the learning rate of 0.0002. We also keep a track of the loss and the accuracy of the training process inorder to track the effectiveness of our model.

network.predict(x) takes in the input vector **x** and feeds it to the neural network. The forward propagation is done, and the predicted value is stored in **prediction**. The loss is calculated, and then the backpropagation step is done using **loss.backward()**. The optimizer is invoked which changes the weights and biases inorder to reduce the loss function. We assume an error of ± 20 kW is acceptable and a prediction within this error range is acceptable.

```python
num_epochs = 10000
log_epochs = 100
learning_rate = 0.0002
lossfunc = nn.MSELoss()
optimizer = optim.Adam(network.parameters(), lr=learning_rate)
loss_hist = [0] * num_epochs
accuracy_hist = [0]*num_epochs
for epochs in range(num_epochs):
    count = 0
    for x, y in train_dl:
        prediction = network.predict(x)
        loss = lossfunc(prediction, y)
        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
        loss_hist[epochs] += loss.item()*y.size(0)
        if(torch.abs(prediction - y) <= torch.tensor(20)): count += 1

    loss_hist[epochs] /= len(train_dl.dataset)
    accuracy_hist[epochs] = count/len(train_dl.dataset)
    if epochs % log_epochs==0:
        print(f'Epoch {epochs} Loss 'f'{loss_hist[epochs]:.4f}')
        print(f'Epoch {epochs} Accuracy 'f'{accuracy_hist[epochs]:.4f}')
```

Listing 3: Training the Model

```python
plt.plot(loss_hist)
plt.plot(accuracy_hist)
test_predictions = network.predict(X_test)
print(X_test[50])
print(test_predictions[50])
```

Listing 4: Checking the loss and accuracy over 10000 epochs and making predictions

We track the loss and accuracy over the 10000 iterations, and plot the data. The results have been discussed in the forthcoming section.

4 Results and Discussion

The plots for the loss function and accuracy of the predictions over 10000 iterations is shown below.

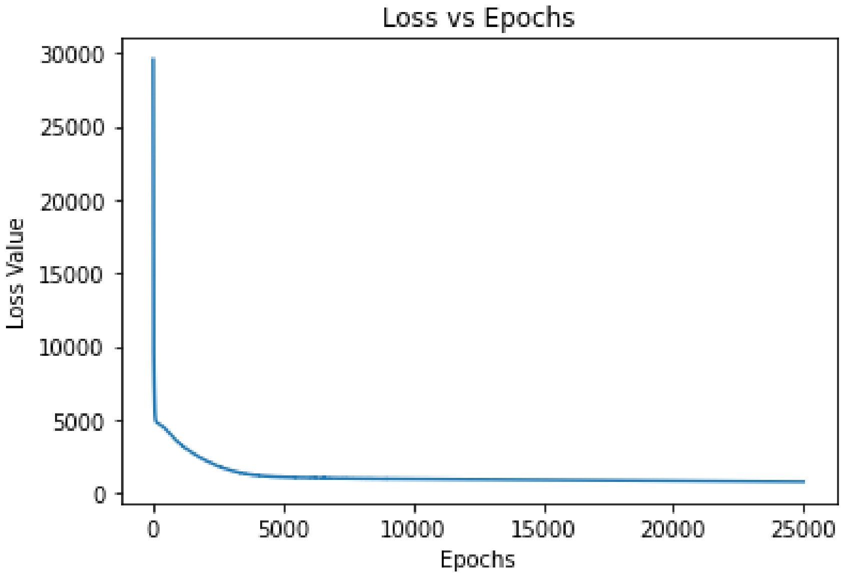

Figure 14: Plot of Loss vs Epochs (decreasing trend is observed)

We can see that our optimizer has reduced the loss, and increased the accuracy. Therefore, we can conclude that our model is performing as expected. The accuracy achieved on the training set is *placeholder value%* after training the model for 10000 epochs.

The objective of this study is to predict the net output power (kW) from the systems derived from various kinds of biomass feedstocks under atmospheric pressure and various operating conditions. The results show how the generated power through the downdraft biomass gasification integrated with power production plant can be successfully predicted by applying a neural network with 40 hidden neurons in the hidden layer and using back-propagation algorithm. The model is applicable for a wide variety of feedstocks.

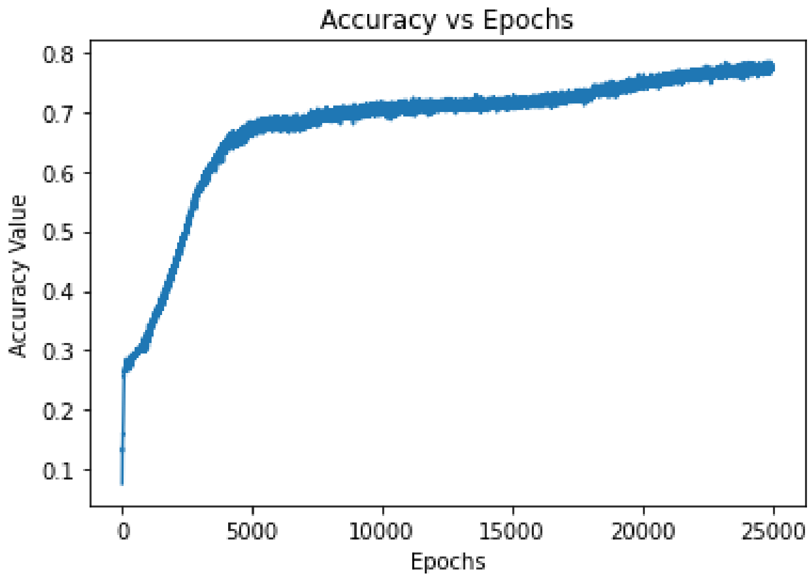

Figure 15: Plot of Accuracy vs Epochs (increasing trend is observed)

5 Further Work

We have been able to use the fully connected feed forward neural network built using PyTorch, to make accurate predictions of the output power generated based on the 11 input parameters of Moisture Content (wt%), Volatile Materials (wt% dry basis), Fixed Carbon (wt% dry basis), ash (wt% dry basis), Carbon (wt% dry basis), Oxygen (wt% dry basis), Hydrogen(wt% dry basis), Nitrogen (wt% dry basis), Sulphur (wt% dry basis), gasifier temperature, Gasifier Temperature (°C) and air to fuel ratio (kgair/kgdrybiomass). Currently, we have over 1000 datapoints over which this neural network is being built. One way to improve upon the results achieved in this work would be to include more experimental data for the biomass analysis and output power generated. This can lead to more accurate predictions of the power generated.

Further, this work can be extended to simulate power production upon combustion of syngas produced from pyrolysis of plastic waste. The Proximate and Elemental analysis can be carried out for different kinds of plastic wastes, which can then be fed to the feed forward network inorder to make predictions on the output power (kW).

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