Analyzing End of Life Tyre (ELT) Carbons Using Machine Learning Algorithm

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***Abstract*: Waste tyre constitute a large percentage of wastes that affect the ecosystem. With an approximation of 1.5 billion tyres reaching their end of life every year, it is important to critically understand what constitutes waste tyres. End of life tyres commonly called ELT has given researchers lot of concerns with understanding it, how it operates and how to better recycle it. This paper is one of such contribution to help with understanding the compositions of ELT tyres but specifically on different carbons produced from ELT tyres. Obviously, carbon is the most dominant and useful remnant of such waste, but In this paper we examined 3 types of end of life tyre carbon, namely IB 550A, IB 330B and IB 660C and their characteristics. We used Machine learning Algorithms to differentiate these carbons base on their chemical composition, to understand all the constituents. This study gives insight on different carbons derived from waste tyres and its composition. It furnishes us with information on the future utility of waste tyres based on the class of carbon it falls under based on our machine learning clustering model and the best utility for each class. With most studies on waste tyres using chemical processes and methodologies to understand waste tyres carbon, a machine learning approach introduces an entirely new approach.**

Keywords: carbon, End of life tyres(ELT), tyre waste, machine learning

INTRODUCTION

Rubber is a very important raw material for development of many important tools and equipment that have been beneficial to man, of the many important tools and equipment that has been produced using rubber, car tyre has become one of the most significant. Its significance is further intensified by the growing rate of 21st century civilization[1]. Where vehicles have become integral to daily living, both for mobility and other logistics. The implication of this high demand and reliance on rubber, also poses a problem in itself[2].

The problem is not further any different, from the problem associated with rubber and its by products, which remains the problem of waste. As rubber and in this specific case tyres reach their end of life, the problem of what next becomes a big question. End of life of tyres (ELT) is a state in the life cycle of a tyre when its significance utility has tremendously dropped, such that it may not be good for further usage in the recycling of further tyres. In the case of tyres for example about 1.5 billion waste tyres reach their end of life every year, a study shows that of the many vehicles using tyres cars have been the one producing the highest amount of waste tyres, this is why in this study more attention will be given to tyres that are from this category. So the big question remains what should we do with these myriad of tyres as they approach their end of life?[3] What constitutes the carbons derived from ELT tyres? This question has been answered in many ways by different researchers, experts and stake holders in the recycling space.

In some places, most especially in the EU the government has legislations that helps with offsetting tyres waste as they approach ELT[4]. In Britain for example they operate a free and open market for waste tyres. This approach deployed by these governments has produced about 95% to 100% reduction in tyres that constitute problem to the ecosystem[5]. Some stake holders use such waste tyres for sound proofing systems. Others use it for creating playgrounds that are rubberized and used by children and for other recreational activities. Others have resorted to the use of rubber for landfills, while initially this landfill method was presumed to be harmless, but recent studies have shown that waste tyres rubber as landfill poses inherent problems to the environment than presumed[6]. One of such problem is the problem of leaching, this leaching causes toxins to leach down to the water and even other soil areas. Therefore, affecting the water and edaphic contents of the land, which is a big problem to both the aquatic life and other edaphic life. This has led to a recent EU ban on landfill method of disposing waste[7].

One thing is consistent in the different approaches to recycling or disposing waste tyres at ELT, and that is the importance of research and understanding more about the composition and behavior of waste tyres at its end of life. The more research and understanding of this phase, the more we can easily build better approaches for either conservation of waste tyres, disposal, processing etc. This paper will focus on this, but specifically on understanding the carbons produced from ELT tyres.

1. Examine critically different end of life tyre carbon wastes
2. Use machine learning to properly decipher the behavioral patterns of these
3. Derive insights from the observed behavioral patterns
4. Suggest probable usage of these tyres waste based on the insights generated from our machine learning model.

LITERATURE REVIEW

The body of contribution by different authors and researchers on the topic of tyre waste has been immense and even ELT. However there were fewer papers trying to understand carbons of ELT tyres using machine learning method. This made our research work much more important as the contribution to the body of works becomes pellucid. However there were several authors whose works were related to our study and whose contributions were very helpful in our approach as well. Some of such contributors and their contributions are:

Chigozie Nwankpa et al 2021, in their paper "Achieving remanufacturing inspection using deep learning", proposed a comprehensive approach to using computer vision to inspect and sort different wastes, especially end of life tyres, for immediate detection and sorting of different EOL(end of life)wastes. A ResNet Architecture was used for this process and using Matlab they obtained a 100% validation in detecting EOL wastes, which helped with easy sorting of these wastes. This performance of their model was also sustained when done with live video images, it was able to still detect EOL efficiently. This research work is ground breaking on how a branch of machine learning could be used in the EOL waste detection and management, a ground breaking feat which lays foundation upon which our study permeates on[8].

Mingyan Gu et al 2010, tried to study the combustion behavior of pulverized waste tyres. Using Fourier transform infrared (FTIR) and simultaneous gas decomposition they were performed experimental tests to study the combustion behavior of tyre waste. Their study showed that for pulverized coal derived from waste tyres, devolatisation begins when the temperature is higher and that when PWT is added it tremendously reduces the devolatisation temperature of the fuel[9].

M.S.H. Mohd Sani et al 2012, in their paper "Assessment on Compressive Strength of Waste Rubber Tube Tyre (WRTT) Fiber in Concrete" studied the strength of waste tyre as it reaches its end of life cycle and how this property can be used in the construction of concrete. In their research they found out that waste rubber tube tyre fiber is low in density when compared with gravel and sand. It showed how immiscible waste tyres are with fresh concrete, and concluded that base on the strength of waste tyre it could be used to replace reinforcement bar inside concretes[10].

Alkhatib et al (2015) did a study on the pyrolysis of End of Life Tires (ELT), in that work pyrolysis of End of life tyres was done on two separate fixed bed reactors having different modes, the objective was to investigate the physical and chemical properties of the tyre. The conclusion from their study has it that pyrolysis of ELT and the result were used to compare with the fuel properties of diesel[11].

Before discussing tyres in the ELT phases, it is also important to understand their general characteristics and composition before this stage, this is exactly what Wajahat Kazmi et al 2019 did, when they used text detection together with some other deep learning methods in this case CNN and HOG to detect and recognize tires[12]. This approach was much novel and different from the conventional use of chemical properties and physical to classify and detect tires. It is this same approach that our paper seeks to further on, but rather this time we pay attention to detecting the properties of carbon waste tyres in their ELT phases using simple machine learning methods.

METHODOLOGY

In this study the goal is to easily detect and classify different carbons derived from ELT tyres using a machine learning method of our choosing. In this paper we focused on three different carbon types that are produced from ELT. Namely the IB 550A, IB 330B and IB 660C carbons.

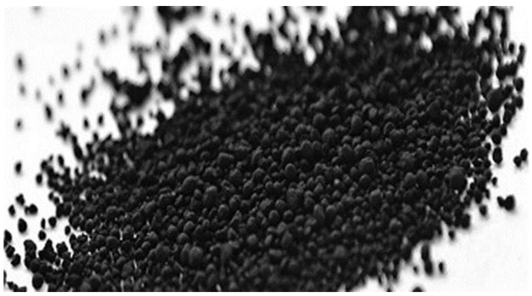


fig: IB 550A, IB 330B and IB 660C range of carbons

These tyres are of some of the finest quality set of carbons produced from tyres that are in their end of life. A flow chart of our process can be seen below.

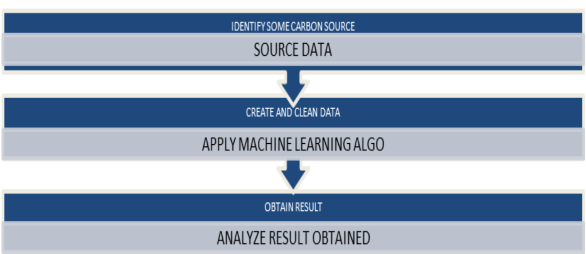


Fig 2: Flow chart describing the study methodology

The first stage of this study involved identifying the carbon type to be used for the study, we tried identifying different carbons produced from ETL, we were able to identify different set of carbons produced by different sources, but of all, we settled for carbon produced by Finister Carbon Mumbai. The range of diversity in their carbon types and the proximity to getting these data were important factors for us in choosing their carbon and we settled to study the chemical properties of IB 550A, IB 330B and IB 660C carbons.

Next was data sourcing, after identifying the data we went ahead to source the data and carbon from this company. After weeks of communication and processing we were able to get some sample from them. Step 3 involved These samples were subjected at least 10 times to different chemical and physical tests and examinations to determine its composition and behavior. We tabulated the result of this tests to document the physical characteristics and components of these tyres. The result were generalized and tabulated as follows.

Characteristics	IB 550A	IB 330B	IB 660C
Physical Appearance	Fluffy Powder	Fluffy Powder	Fluffy Powder
N_2SA (m_2/kg) (BET method)	> 51	> 78	> 45
Iodine No. (mg/g)	> 60	> 82	> 55
Density (g/cc)	< 0.20	< 0.15	< 0.25
Particle Size (µm)	< 20-25	< 15-20	< 20-30
Heating Loss (Max)	< 1	< 1	< 1

Table1.0: summarized table of different EOL carbons

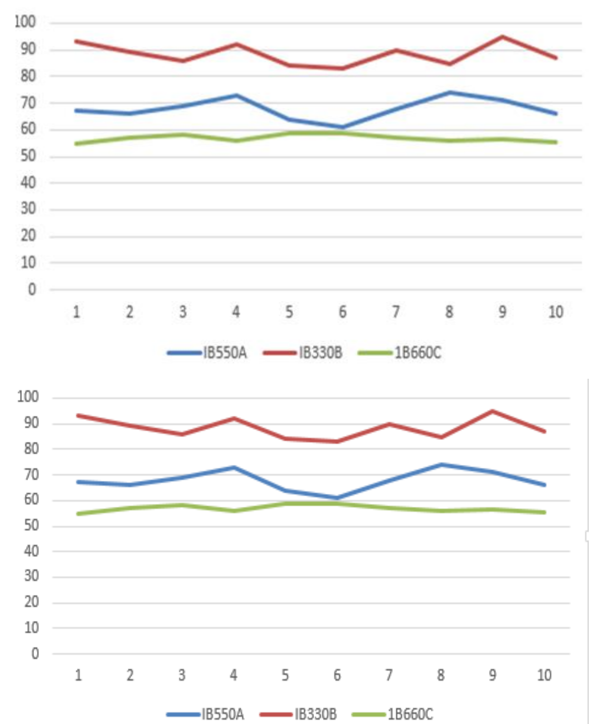


Fig 3: Graphical illustration of Iodine and N2SA results obtained

The data obtained were cleaned for it to be suitable for running a machine learning algorithm on it. Data cleansing means we removed inconsistent data and data that was not in the range of our investigation.

The next step involved applying a machine learning algorithm on the collected data, the machine learning model applied here was a simple K-means model. K-means is a very popular machine learning algorithm, it finds the centroid of a given data set, it is an unsupervised learning model and is mostly used for clustering purpose[13].

K-Means was used to create a cluster of performance or attribute of each of the carbon type that we will be examining. With this model it becomes easier to easily visualize and pictorially describe the differences that exist in each carbon class under examination[14].

Subsequent upon subjecting the data to thorough investigation, examination and modelling we were able to obtain some results. We created a model for the following chemical components found in the carbons under analysis[15].

(i) N2SA
(ii) Iodine

We also did a modelling for the physical properties of the different carbons some physical properties we observed were[15].

(i) Density
(ii) Particle size

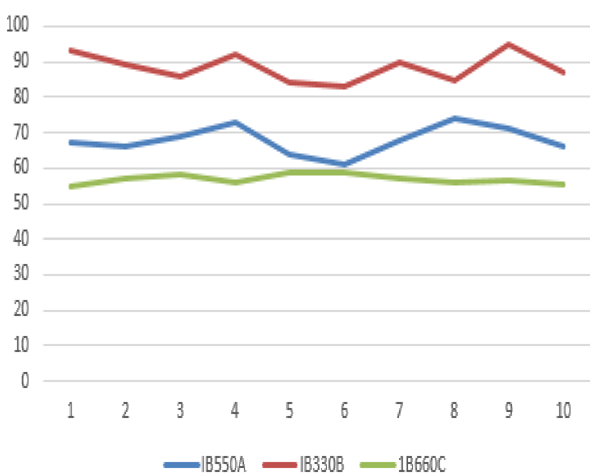


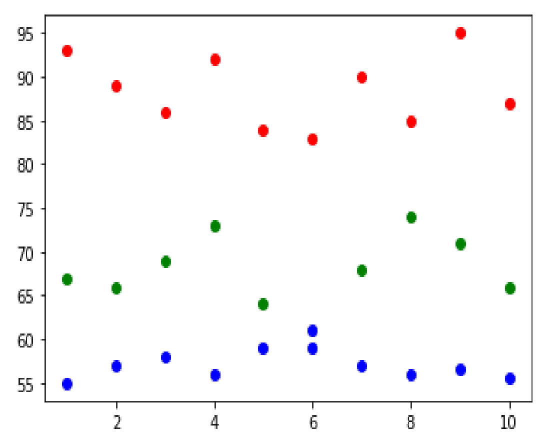
Fig4: Graphical illustration of the density of the different carbon components

Fig5: Graphical illustration of the particle size of the different carbons

For each of the properties above, the results obtained can be seen in the images below. The physical appearance of carbon and the heat loss were not subjected to any test, because these were the same for all carbon types[16].

RESULTS AND DISCUSSION:

There are many ways to analyse the physical and chemical components of an element, in this study we incorporated machine learning algorithm as well to this process, particularly to observing the carbons synthesis from tyres ELT[17]. The addition of machine learning to the results obtained through chemical analysis and physical observation improved our understanding of the results obtained through chemical and physical observations. This we can say is the first effect of subjecting physical and chemical data to machine learning modelling, it optimizes the result and improves our understanding of the data[18].



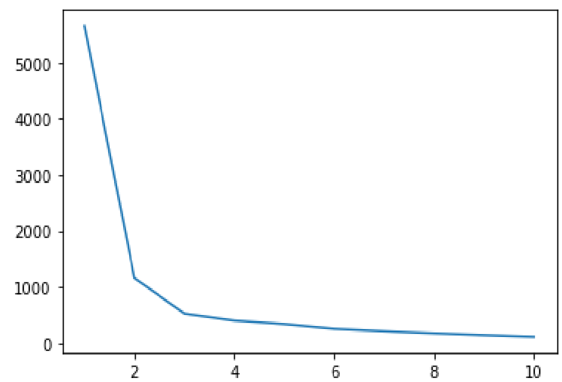
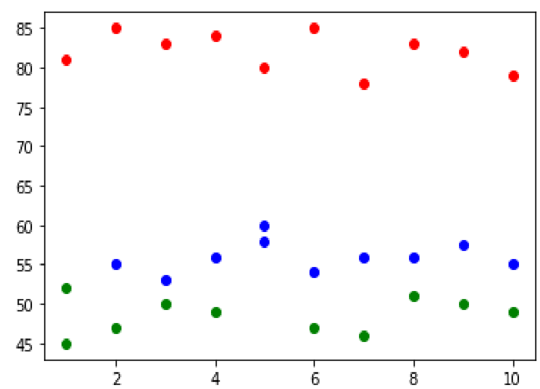


Fig 6: K-means result for Iodine component of the different carbons



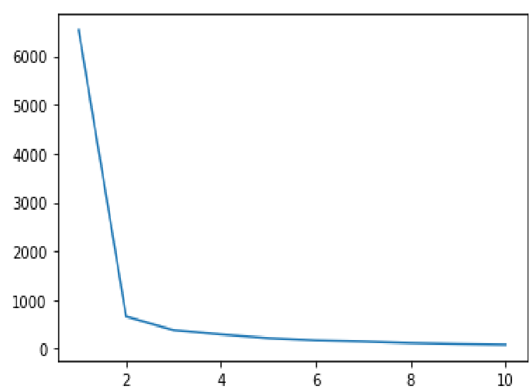
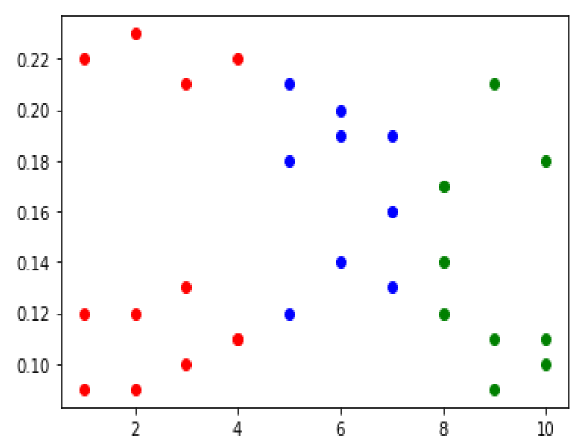


Fig 7: K-means result for N2SA component of the different carbons

From our result it can be observed that with respect to the N2SA component of IB550A, IB330B, IB660C class of carbons the centroid for each of this is at 57, 82 and 49 (m2/kg). The centroid here gives us an idea of where most N2SA elements in the carbon class are likely to belong to, the centroid in these results can be obtained by finding the point in each class where most of the points revolved around, it is a point in space where most data points fit in. It gives an average value where most of the element belong to. For Iodine the centroid for the same classes were at 66, 84 and 57 (mg/g) respectively, again this helps us decipher easily the average and likely amount of Iodine to be found in each carbon class. As part of the observations we can also that IB330B is high in N2SA and Iodine as compared with the other carbon types. This gives us an idea that in the utilization for carbon black derived from waste tyre, if either the properties of N2SA and Iodine are of prior importance its application or usage then IB330B carbon would be more ideal for such application. Where a minimal or lower amount of these compounds are needed then IB550A and IB660C may be considered. A table describing the chemical components with respect to the centroids obtained

CHEMICAL COMPONENT	IB550A	IB330B	IB660C
N2SA (m2/kg)	57	82	49
IODINE(mg/g)	50	83	56

Table 2.0: Centroid of the chemical components of different carbon class



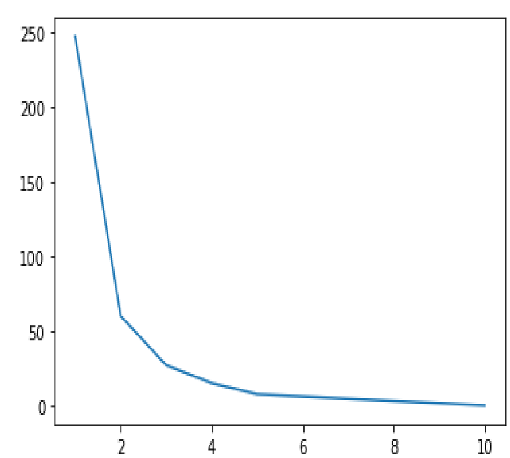
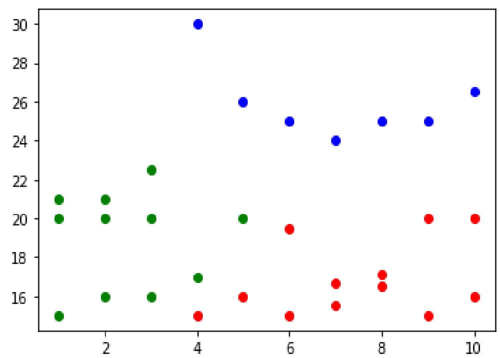


Fig8: K-means result for the density properties of the different carbons



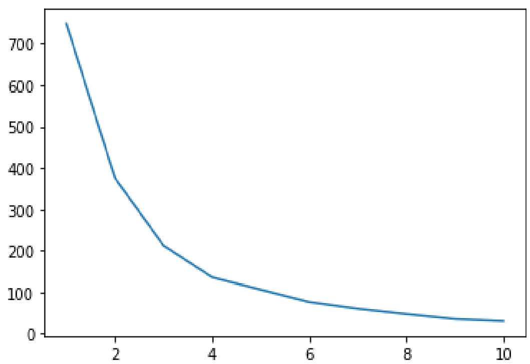


Fig9: K-means result for the physical sizes of the different carbons.

Also from our result, we obtained the centroid for the different physical components of IB550A, IB330B, IB660C carbons. Our result for density for each of the carbon class is 0.18, 0.17, and 0.22 (g/cc) respectively, with respect to the size we had 20, 17 and 25 (µm) respectively. The result obtained shows the likely precise range of value for the density and size of IB550A, IB330B, IB660C. Where a more precise value is needed with dealing with this element, in either mode of applications then the result gotten from this using machine learning(K-Means Algorithm) becomes quintessential. Also observatory results from the result also reveals that IB660C has higher density and particle size as compared to the other class of carbons in observations[19]. Where larger and more granular carbon is needed, IB660C will be more ideal for such usage. Where finer carbon is need IB330B should be preferred and where a moderately fine size is needed IB550A is recommended[20]. A table showing the centroid of the physical components can be seen below.

PHYSICAL QUALITY	IB550A	IB330B	IB660C
Density(g/cc)	0.18	0.17	0.22
Particle Size(µm)	20	17	25

Table3.0: Centroid of the physical components of different carbon class

From our study, we realize that we could sufficiently predict the centroid for each of the carbon class with respect to some critical compositions and qualities under observation. The centroid does not take away the range of the values that this carbon compound can fall alongside, but focuses on predicting a value which most of it falls within. This approach becomes very important when dealing with these compounds in cases where precision is very important. Also it helps gives pictorial representation of the data in ways in which all the data makes more sense as opposed to using ranges of numbers which can be a bit problematic to some persons while using such data.

CONCLUSION

Applying K-means to date obtained from carbon produced from tyres in their end of life gave us some optimal results that were not possible using just the routine chemical and physical investigative methods. We were able to move away from just giving a range of what the values is to finding the centroid and most common of the values. Our result indicates that implementation of machine learning on the received sample optimized the result made it simpler and much more visualized. This helps gives more insight to the data, and also gives more understanding of the data. At the end of this study we can say sufficiently that were able to actualize all our project objective, with relevant result as well.

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