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Machine learning based metal recovery from the waste printed circuit boards of mobile phones for circular economy and sustainable environment

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ABSTRACT

The metal recovery from the waste printed circuit boards (WPCBs) of mobile phones presents reduced reliance on natural resources, savings in energy and emissions discharge complemented with economic incentives as well. Herein, we present a machine learning (ML) based model for Cu, Ni and Pb recovery from the WPCBs of mobile phones using low temperature roasting process. The ML model for the metal recovery is built using Artificial Neural Network (ANN) where three variables (roasting temperature, roasting time, NH_4Cl dose) are used as inputs for the model. The model-based significance order of the input variables is obtained by computing partial derivatives of outputs with respect to the inputs. Temperature is the most significant input variable for Cu while time is the most significant variable for Ni and Pb recovery, contributing the percentage significance of 42%, 41.3% and 48.4% respectively. The proposed ML based analysis framework can be deployed for enhancing the insights about the metal recovery process contributing to the smart operation and operational excellence.

Keywords: Metal recovery, printed circuit board, machine learning, environmental sustainability, circular economy

NONMENCLATURE

Abbreviations	
ANN	Artificial Neural Network
ML	Machine Leaning
WPCB	Waste Printed Circuit Board

1. INTRODUCTION

Mobile phones have become an integral part of day-to-day life for communication as well as internet access. However, rapid technological innovations have reduced the life span of mobile phones and the average life span of mobile phones is around 2-3 years thereby millions of mobile phones are discarded every year [1]. Printed circuit boards are one of the essential components of mobile phones. Therefore, end-of-life mobile phones also generate waste printed circuit boards (WPCBs). WPCBs of mobile phones contain valuable metals (Au, Ag, Pt, Pd, Cu, etc.), harmful metals (As, Pb, Ni, etc.) as well as halogenated flame retardants [2]. Moreover, the concentration of valuable metals in WPCBs of mobile phones is higher than that of the ores [3]. The presence of toxic materials in WPCBs of mobile phones makes them a potentially hazardous substance and improper treatment of WPCBs can result in environmental pollution.

In the literature, different approaches such as pyrometallurgy, hydrometallurgy, and biohydrometallurgy have been employed for metal recovery from WPCBs. However, the limitations associated with these technologies have hampered their widespread industrial application. Pyrometallurgy is an energy-intensive process and also results in the generation of toxic gases [4]. Hydrometallurgy majorly uses strong inorganic acids for the recovery of metals which generates secondary pollutants and can result in environmental pollution as well as human health concerns [5]. Biohydrometallurgy is a greener approach compared to pyrometallurgy and hydrometallurgy. However, the possibility of contamination of microorganisms and their sensitivity to temperature and pH along with slower reaction kinetics are the drawbacks which should be addressed for the industrial application [4]. Therefore, it is important to develop a sustainable process for the recovery of metals from the aspect of resource conservation, environmental protection as well as the creation of a circular economy. In this regard, low-

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temperature roasting is a promising and eco-friendly process for the recovery of metals. It has advantages such as high metal recovery, low energy and cost requirements, and negligible generation of toxic gases and effluents. This provides an edge to the low-temperature roasting process over conventional hydrometallurgical and pyrometallurgical approaches.

Trivedi and Hait [6] investigated Cu, Ni, Pb, and Zn recovery from the WPCBs of mobile phones using bio-Fentom process. The response surface methodology technique was applied to maximize the metal recovery. Cu recovery from WPCBs by complex suspension electrolysis process is analyzed by surrogate and ML modelling and simulated annealing technique was utilized to maximize the metal recovery [7]. Annamalai and Gurumurthy [8] applied bioleaching technique for Cu, Au and Ag recovery from WPCBs and used artificial neural network (ANN) and genetic algorithm framework to estimate the optimized conditions for the metal recovery. In few other research studies, ML is used for the modelling of metal recovery process [9, 10]. However, ML based modelling of Cu, Zn and Ni recovery from the WPCBs using low-temperature roasting process has not been reported in the literature.

In this research, we have conducted extensive experimentation for Cu, Ni and Pb recovery from the WPCBs of the mobile phones using low temperature roasting process and have deployed the dataset to model the metal recovery process by using ML based modelling approaches. ANN process models are developed after tuning hyperparameters for prediction and generalization of the functional mapping between the input-output variables. Later, partial derivative based sensitivity analysis technique is applied to establish the significance order of the input variables. The application of ANN for modelling Cu, Ni, and Pb recovery from the WPCBs promotes the inclusion of machine learning in the domain of metal recovery literature. Furthermore, it is expected that the higher material utilization efficiency achieved through metal recovery processes can contribute to circular economy and sustainable environment.

2. METHOD

Figure 1 presents the methodology adopted in this work to develop the data-driven ML based process models and conducting the significance analysis for Cu, Ni and Pb recovery from the WPCBs of mobile phones. The experiments are designed on the different levels of three input variables namely roasting temperature, roasting time and NH_4Cl dose. The WPCBs of mobile phones were initially shredded and crushed to the size of 1 mm. The crushed WPCBs were then further pyrolyzed at 400 °C for 30 minutes in a fixed bed reactor for the degradation of the polymeric fraction. The solid product obtained after the pyrolysis was further subjected to the NH_4Cl roasting in the presence of air. The recovery of metals during the roasting process depends upon the roasting temperature, roasting time, and NH_4Cl dose. Therefore, the effect of these process parameters was investigated by varying the roasting temperature from 200 to 325 °C, roasting time from 1 h to 5 h, and NH_4Cl dose from 1 to 4 g/g pyrolyzed WPCBs. The metals present in the pyrolyzed WPCBs are converted to metal chlorides during the roasting process. The solid residue of the roasting process containing metal chlorides was further subjected to the water leaching at 80 °C for 30 min to extract metals. Finally, the slurry obtained was filtered and the filtrate was analyzed to determine metal recovery. The procedure is repeated on the designed experiments and the metal recovery dataset is compiled. The % recovery of metals was determined using the equation (1).

$$\%\ Metal\ Recovery = \frac{Amonut\ of\ metal\ in\ filtrate}{Initial\ amount\ of\ metal\ in\ pyrolyzed\ PCB}\ x\ 100 \qquad (1)$$

The collected dataset is visualized to assess the data-distribution space as well as identifying the linear dependence among the input variables. The data-distribution space is visualized by plotting the violin plot, and Pearson correlation coefficient (PCC) is calculated to investigate the variables' dependence. The value of PCC varies from -1 (strongly negatively correlated) to +1 (strongly positively correlated); whereas, PCC = 0 indicates the absence of linear relationship between the two variables thereby the independent input variables can be selected. In the next step, machine learning model is trained on the collected dataset by artificial neural network (ANN) model – a powerful modelling algorithm of ML that can capture the nonlinearity and complex causal relations among the variables and the effective functional mapping between the input-output variables can be constructed. The predictive performance of the ANN model is evaluated on the two statistical performance indicators, namely co-efficient of determination (R^2) and root-mean-squared-error (RMSE) commonly used for the ML based studies [11]. Thus, a well-predictive ANN model possessing good generalization performance is selected for Cu, Ni and Pb recovery. Later, the developed ANN models for the metal recovery are deployed for the investigation of input variables' significance on the metal recovery from the WPCBs by partial derivative approach [12]. A comprehensive analytical framework comprising extensive experimentation for the metal extraction from the WPCBs, ML based model development and variables' significance analysis is presented to enhance the understanding about the metal recovery process.

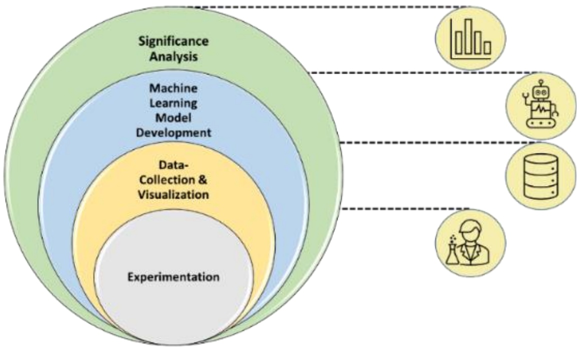

Figure 1. The methodology adopted to carry out this study that comprises on several analytical stages.

3. RESULTS

3.1 Data-collection and Visualization

Fifteen experiments are designed on the wide-operating ranges of the input variables and are carried out to recover Cu, Ni and Pb from the WPCBs of mobile phones. The metal recovery dataset corresponding to the experiments is compiled that serves as the data to develop the ML model. The data-distribution space of the metal recovery with respect to the roasting temperature (Temp.), roasting time (time) and NH_4Cl dose is presented in Figure 2. Roasting temperature is changed from 200 to 325 ^oC roasting time is maintained from 1 to 5 h while NH_4Cl dose is varied from 1 to 4 g/g pyrolyzed WPCBs. In response to the variation in the operating values of the input variables; Cu, Ni and Pb recovery varies from 35 to 93%, 46 to 100% and 31 to 100% respectively. A reasonable impact of the input variables on the metal recovery from WPCBs is observed pointing to the relative significance of the input variables. Furthermore, the PCC based heat map suggests the absence of linear relationship among the input variables since the PCC value for the input-input variable is around zero thereby indicating the independent nature of the input variables. The input variables' independent nature is desirable to construct the effective functional mapping among the input-output variables and ensuring the excellent predictive performance of the ML model. Thus, the three input variables are deployed to model the metal recovery process from the WPCBs.

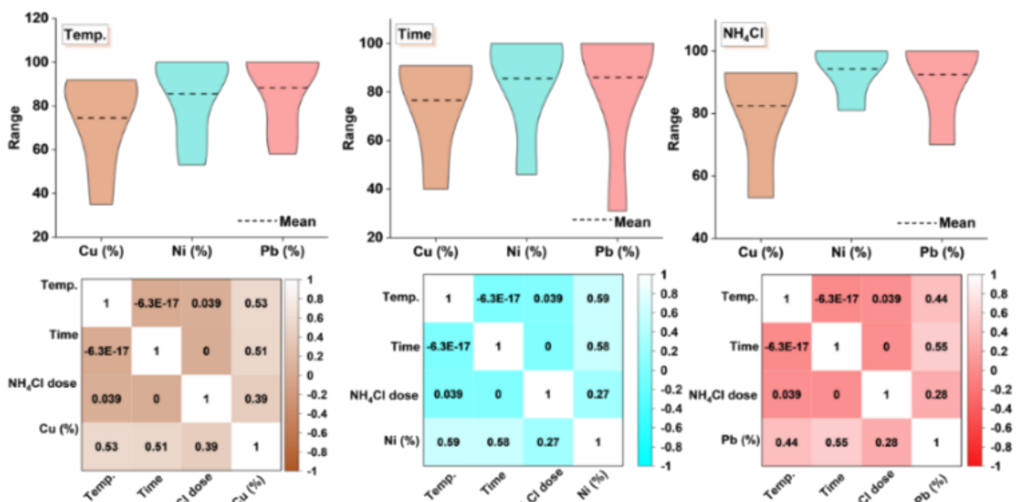

Figure 2. The data-distribution space of Cu, Ni and Pb recovery from the WPCBs with respect to the input variables: Temp., Time and NH4Cl dose. The PCC based heat map constructed for Cu, Ni and Pb confirms the independent nature of the input variables.

3.2 Development of artificial neural network model for metal recovery

ANN is a universal function approximator and can mine the underlying information present in the data for developing the effective cause and effect relationships [13]. The superior modelling capacity of this technique makes it suitable for developing the process models for the complex systems defined on the hyperdimensional input space, taking into account the nonlinear interactions as well [14]. In this work, data split ratio of 0.8 and 0.2 is utilized for training and testing dataset respectively. The hidden layer neurons are varied from 3 to 8 to find the suitable architecture of the ANN model. The tangent hyperbolic function is applied as an activation function on the hidden layer. Whereas, linear activation function is used on the output layer of the

ANN architecture. Gradient descent with momentum algorithm is deployed for computing optimal values of the model parameters. Moreover, early stopping criteria are also established for training the ANN model in MATLAB 2021 b, i.e., change in gradient is less than 0.000001, maximum epochs (1000) and performance goal (0.001) etc., are achieved to avoid the overfitting problem.

Figure 3 presents the modelling performance of ANN with respect to hidden layer neurons during training and testing phase as measured against R^2 and RMSE. The hidden layer neurons are varied from 3 to 8 in the ANN architecture for modelling Cu, Ni and Pb recovery from the WPCBs against the input variables as shown in Figure 3(a-c) respectively. Closely observing the performance of the ANN models for the three output variables, it is found that ANN model having three hidden layer neurons has relatively better predictive performance for Cu recovery as compared to other ANN models. Similarly, ANN models for Ni and Pb having six and five hidden layer neurons have superior predictive performance in comparison to other ANN models respectively. Thus, the ANN models optimized on their architecture are selected and the modelling performance of models for Cu, Ni and Pb recovery during training and testing phase is as follows: for Cu: R^2_train = 0.97, R^2_test = 1.0, RMSE_train = 3.50 %, RMSE_test = 2.98 %; for Ni: R^2_train = 0.96, R^2_test = 0.99, RMSE_train = 3.74 %, RMSE_test = 0.75 %; and for Pb: R^2_train = 0.87, R^2_test = 0.84, RMSE_train = 7.75 %, RMSE_test = 8.10 %.

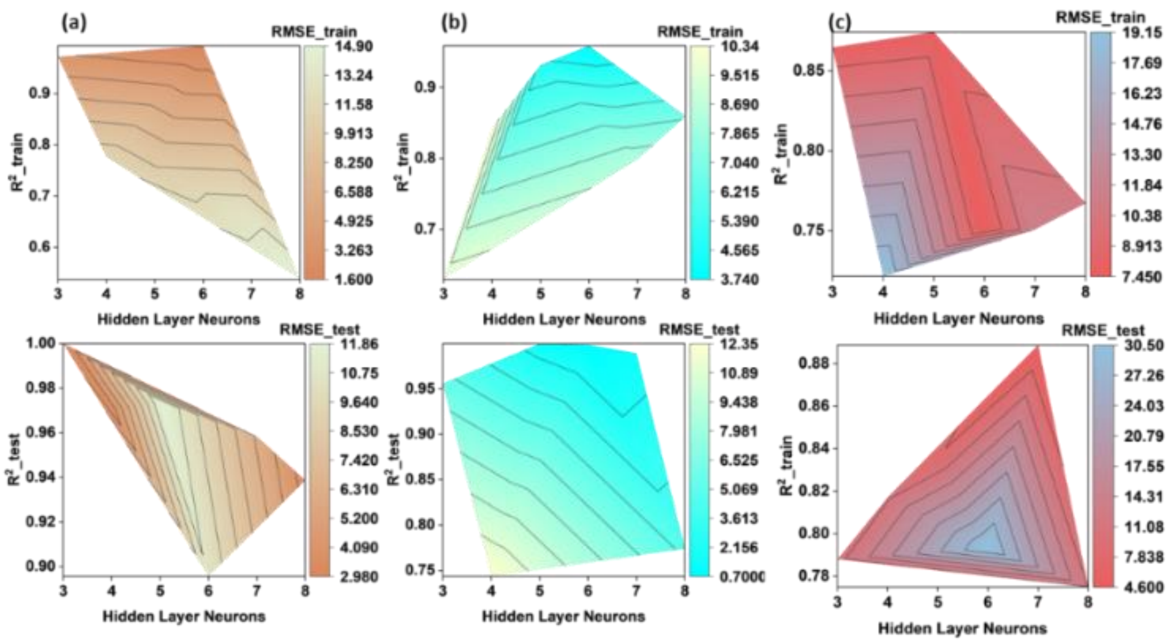

Figure 3. Development of ANN model for Cu, Ni and Pb recovery from WPCBs. The training and testing performance of the models having different hidden layer neurons are evaluated with respect to R2 and RMSE for a) Cu, b) Ni, and c) Pb.

3.3 Significance analysis of the input variables on the metal recovery

The developed ANN model represents the functional approximation of the metal recovery process as constructed on the data collected from the experiments. In the next step, it is imperative to investigate the significance of the input variables on the metal recovery from the WPCBs of the mobile phones. For this purpose, partial-derivative based sensitivity analysis technique is used as it provides the explicit diagnostics of the variables significance on the output variable. The details about the partial-derivative based sensitivity analysis technique can be found in [12].

Figure 4 shows the percentage significance of the input variables on Cu, Ni and Pb recovery from the WPCBs of the mobile phones. Roasting temperature (Temp.) is appeared to be the most significant variable for Cu recovery having percentage significance of 42%. Whereas, roasting time (time) is the most significant variable for Ni and Pb recovery with percentage significance of 41.3% and 48.4% respectively. The relatively least significant input variable for Cu, Ni and Pb recovery is NH_4Cl dose having the percentage significance of 21.3%, 18% and 17.4% respectively. In the present study, decomposition of NH_4Cl starts above 200 °C which results in the formation of HCl and ammonia. The metal present in pyrolyzed WPCBs reacts with HCl in the presence of air and forms metal chlorides. The reactions responsible for the recovery of metals are mentioned below.

$$NH_4Cl(s) \rightleftharpoons HCl(g) + NH_3(g)$$

$$Cu(s) + 2HCl(g) + 0.5O_2(g) \rightleftharpoons CuCl_2(s) + H_2O(g)$$
$$Ni(s) + 2HCl(g) + 0.5O_2(g) \rightleftharpoons NiCl_2(s) + H_2O(g)$$
$$Pb(s) + 2HCl(g) + 0.5O_2(g) \rightleftharpoons PbCl_2(s) + H_2O(g)$$
$$Cu(s) + 2HCl(g) \rightleftharpoons CuCl_2(s) + H_2(g)$$
$$Ni(s) + 2HCl(g) \rightleftharpoons NiCl_2(s) + H_2(g)$$
$$Pb(s) + 2HCl(g) \rightleftharpoons PbCl_2(s) + H_2(g)$$

NH_4Cl roasting helps to recover metals at a lower temperature as well as converts metals into water soluble-metal chlorides which helps to avoid the use of corrosive and toxic solvents for metal leaching. Temperature plays an important role in the NH_4Cl roasting process as it is responsible for the decomposition of NH_4Cl to HCl which reacts with metals. The increase in temperature from 200 to 300 °C results in the maximum recovery of Cu, Ni, and Pb. The complete decomposition of NH_4Cl takes place at around 300 °C which generates maximum HCl. Therefore, the roasting temperature is a significant process parameter for metal recovery using NH_4Cl roasting. Along with temperature, the roasting time (time) also plays an important role in metal recovery. The increase in the roasting time from 1 h to 5 h results in a higher metal recovery. The dose of NH_4Cl is also an important factor; however in this study, it was found that the dosage of NH_4Cl used for experiments is not a limiting factor. The less effect of NH_4Cl on metal recovery compared to temperature and time can be attributed to the presence of an excess amount of NH_4Cl in the system for the recovery of metals.

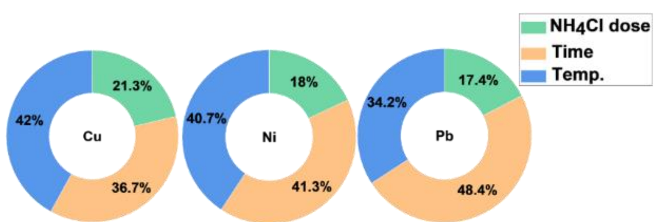

Figure 4. Significance of input variables towards Cu, Ni and Pb recovery from WPCBs using low-temperature roasting process.

4. CONCLUSIONS

In this research, we have presented the ML model based analytical framework to investigate the metal recovery from the WPCBs of mobile phone using low-temperature roasting process. The experimental data collected for Cu, Ni and Pb recovery from the WPCBs is used to model the metal recovery process by artificial neural network. High modelling accuracy with R^2 value greater than 0.83 is achieved to model Cu, Ni and Pb recovery from WPCBs. The partial-derivative based significance analysis reveals that roasting temperature is the most significant variable towards Cu having percentage significance value of 42%. Whereas, roasting time is the most significant variable for Ni and Pb recovery with the percentage significance of 41.3% and 48.4% respectively. In the future work, the ML model based analytical framework would be extended to include the optimization analysis for maximizing the metal recovery and minimizing the cost of metal recovery process to support the circular economy and environmental sustainability.

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DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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