IMPLEMENTING ARTIFICIAL INTELLIGENCE TECHNIQUES TO PREDICT ENVIRONMENTAL IMPACTS

Case of Construction Products

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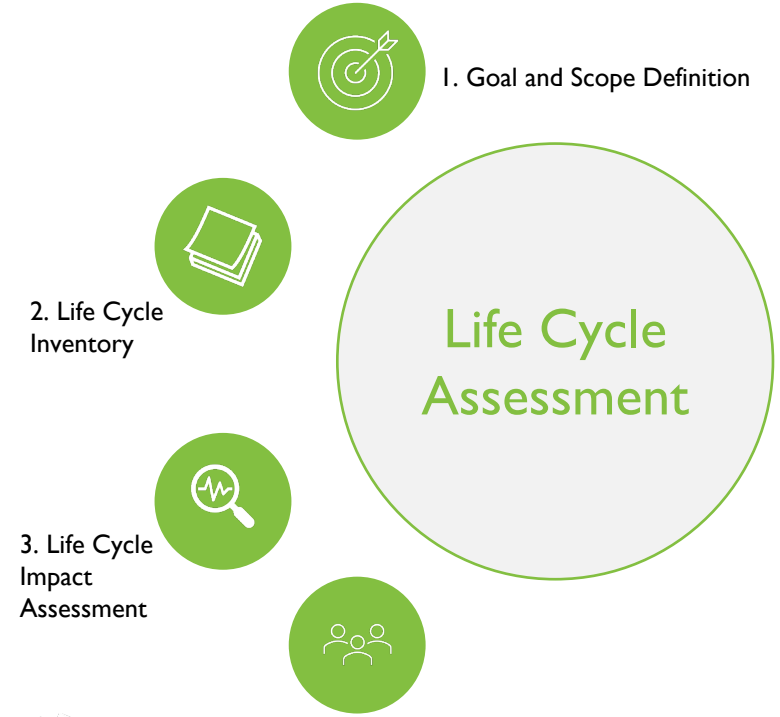
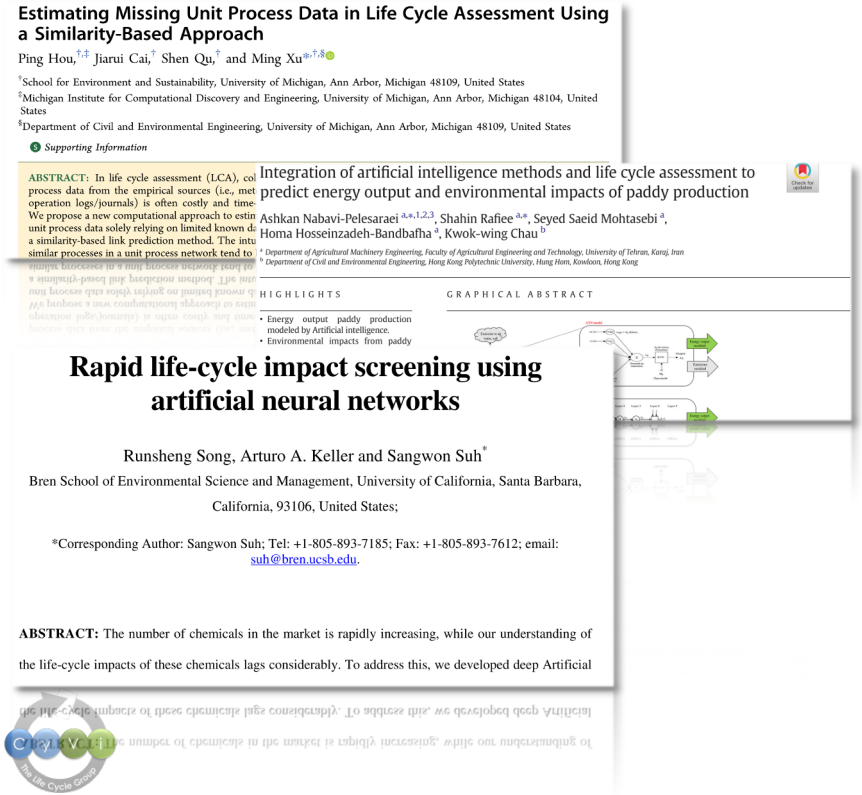
Life Cycle Assessment



Source: ISO 14040

- Requires large volumes of data
- Requires meticulous data modelling and analyses
- Time consuming

Artificial Intelligence in LCA



Estimating Missing Unit Process Data in Life Cycle Assessment Using a Similarity-Based Approach

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Supporting Information

ABSTRACT: In life cycle assessment (LCA), col
process data from the empirical sources (i.e., met
operation logs/journals) is often costly and time-
We propose a new computational approach to estin
unit process data solely relying on limited known da
a similarity-based link prediction method. The intu
similar processes in a unit process network tend to

Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production

Ashkan Nabavi-Pelesaraei [a,*,1,2,3], Shahin Rafiee [a,*], Seyed Saeid Mohtasebi [a], Homa Hosseinzadeh-Bandbafha [a], Kwok-wing Chau [b]

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HIGHLIGHTS

- Energy output paddy production modeled by Artificial intelligence.
- Environmental impacts from paddy

GRAPHICAL ABSTRACT

Rapid life-cycle impact screening using artificial neural networks

Runsheng Song, Arturo A. Keller and Sangwon Suh*

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*Corresponding Author: Sangwon Suh; Tel: +1-805-893-7185; Fax: +1-805-893-7612; email: suh@bren.ucsb.edu.

ABSTRACT: The number of chemicals in the market is rapidly increasing, while our understanding of the life-cycle impacts of these chemicals lags considerably. To address this, we developed deep Artificial

Policy

Growing concern for the environment

Business Incentives

Instant Prediction Model

Environmental Product Declaration

PCR
- Define product
- Find available PCR

LCA
- LCIA results
- ISO report

EPD
- Create EPD
- Verify and publish EPD

Source: EN 15804

FDES VÉRIFIÉE inies

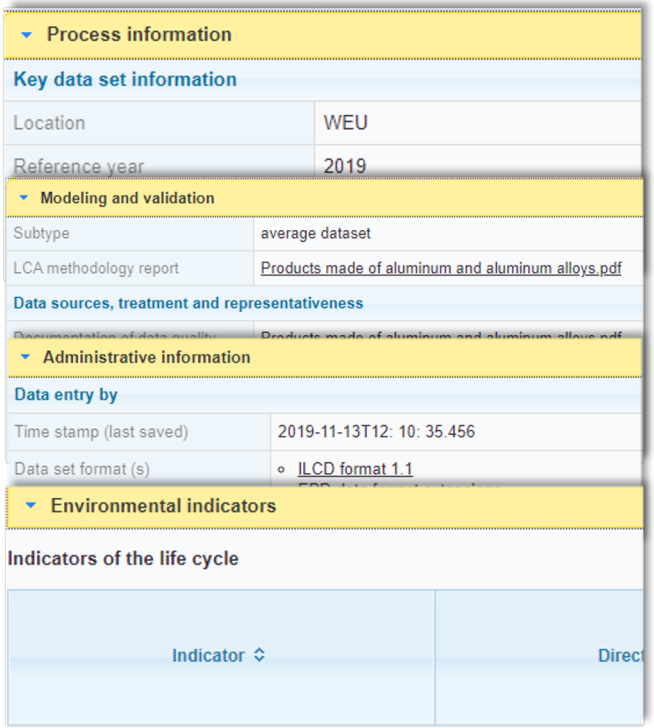
Institut Bauen und Umwelt e.V.

PEP ecoPASSPORT

UL CERTIFIED ENVIRONMENTAL PRODUCT DECLARATION

epd-norge.no
The Norwegian EPD Foundation

EPD®
THE INTERNATIONAL EPD® SYSTEM

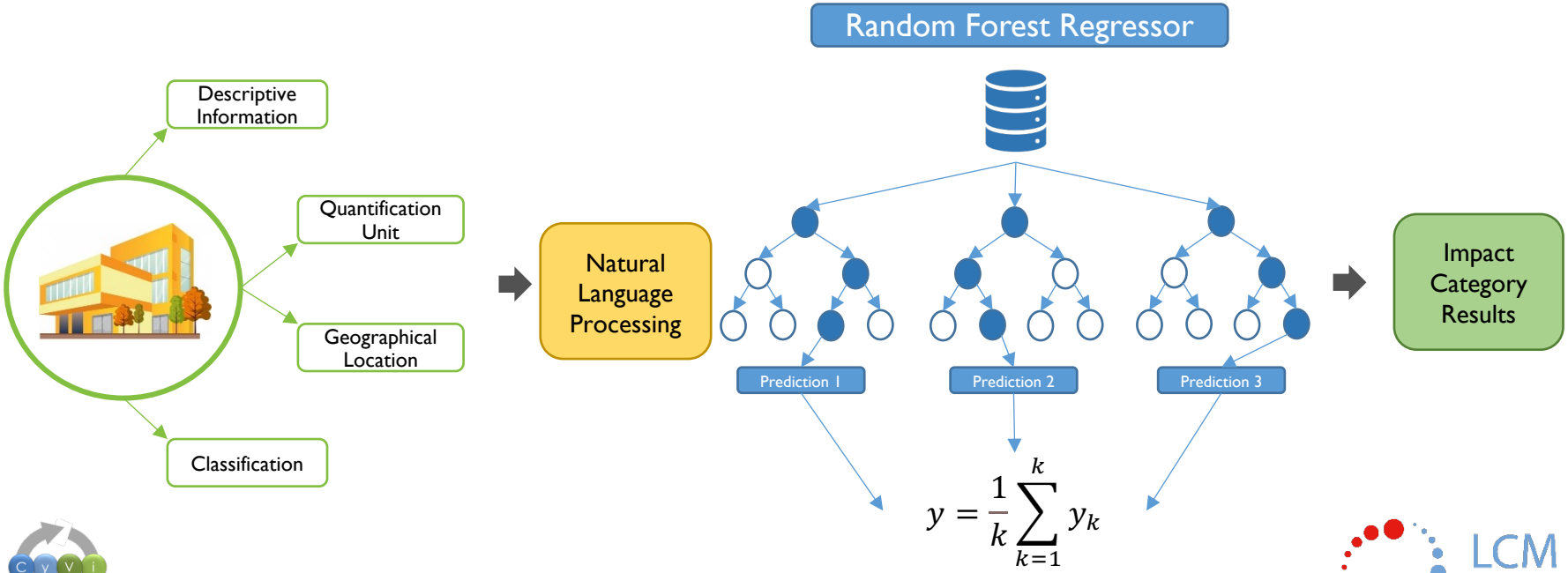


Source: Ökobaudat - IBU

LCM 2021

Prediction model

Prediction of Life Cycle Impact Assessment results for construction materials



Variable distinction

Name

Quantification Unit

Descriptive Variables

Data construct as a sentence or paragraphs that requires treatment before analyses

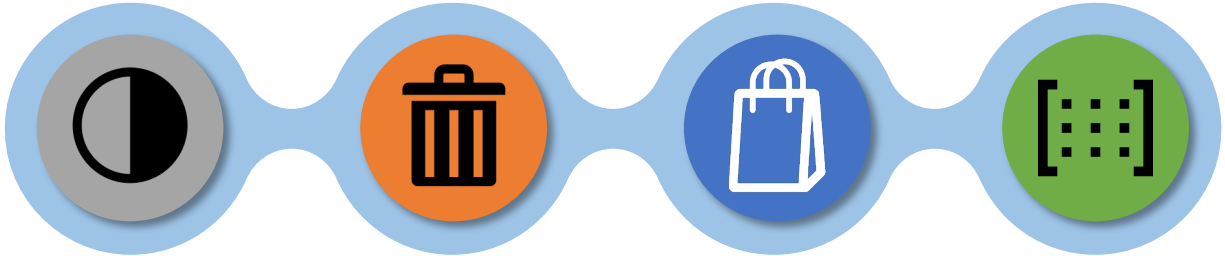
Location

Classification

Categorical Variables

Data ready to use into the model with few modifications

Natural language processing



Split the data

Breakdown the sentences into words

Remove stop words

Remove short function words such as the, is, at..

Bag of words

Prepare a list of all the words in all the variables

Matrix

Count vectorize words for each variable

Variable	product	seal
1	1	1
2	0	0
3	1	0
4	1	1
5	0	0

Training and testing dataset

Factorize the variables

Convert the categorical variables into numerical factors

Consolidated database

Combine the factorized variables and the matrix

Split database

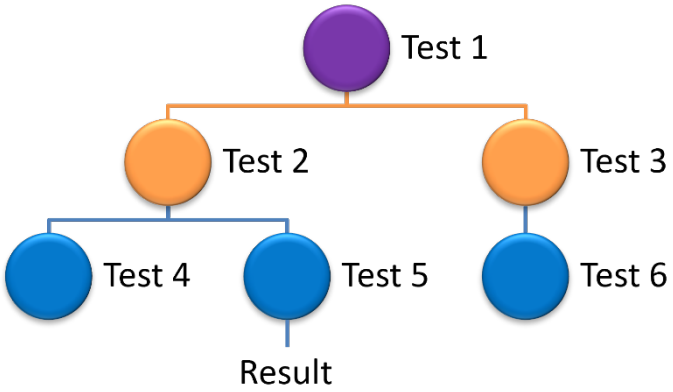
Split the consolidated database into training and testing datasets

80% Training dataset

20% Testing dataset

Random forest regression

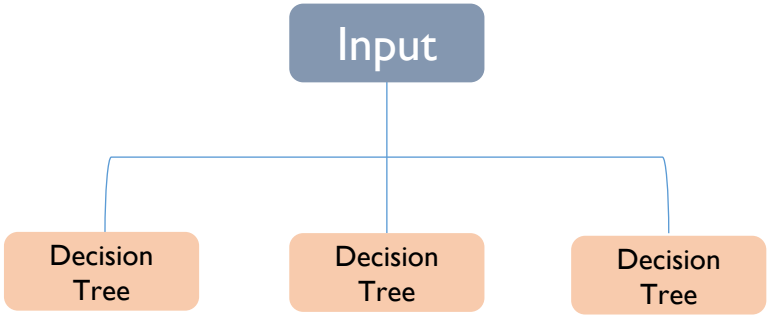
Decision Tree



Can handle large database

Aggregated results

High accuracy



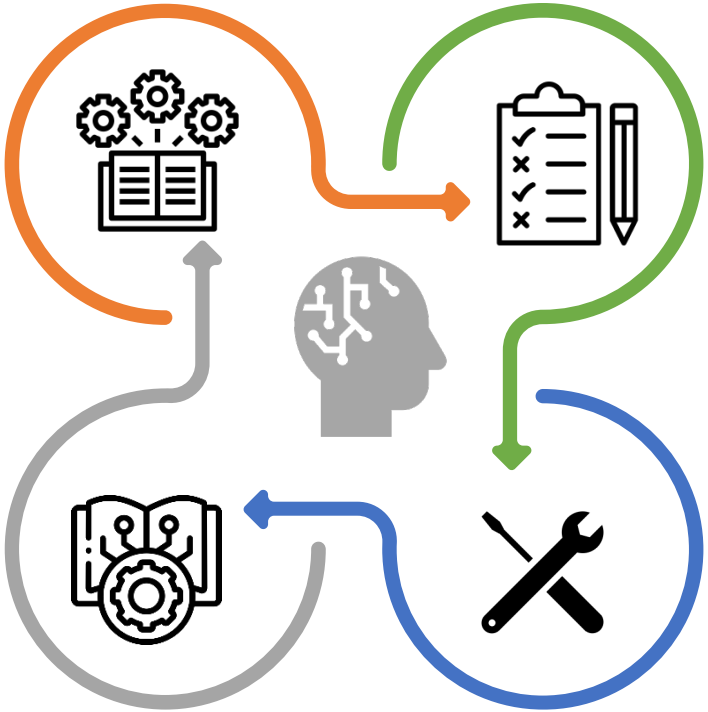
Training and hyperparameter tuning

TRAINING

The prediction model is trained with the splitted 80% data of both input and output variables

TESTING

The testing phase observes the anomalys and effectiveness of the tuned model



VALIDATION

An algorithm verifys the unbiased prediction model to assist the hyperparameter tuning

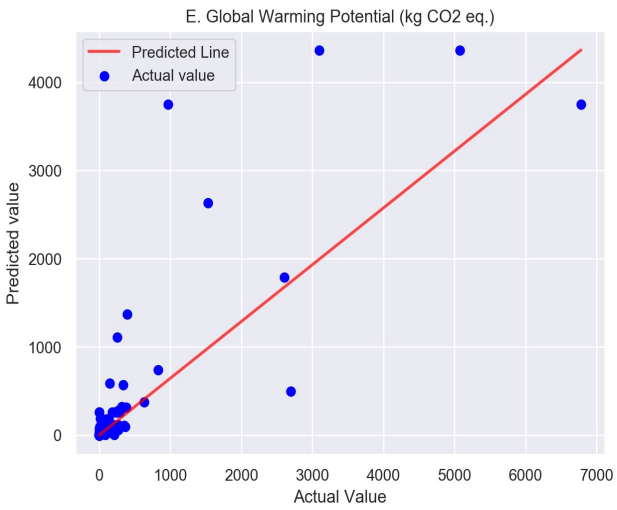
HYPERPARAMETER TUNING

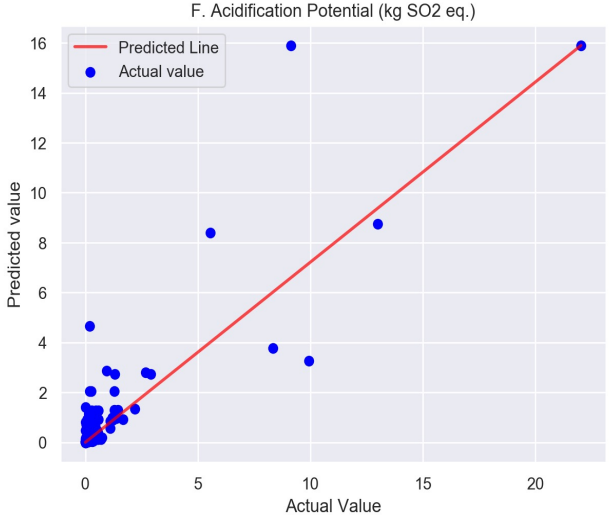
Some parameters control the way the random forest fits and trains the data. Modifying affects the results and can improve the accuracy

Accuracy of the prediction

Impact category	Number of data points	Mean squared error	R-Squared Results
Global warming potential	174	0.28	81 %
Photochemical Ozone Creation Potential	196	0.07	70 %
Acidification potential	196	1.12	68 %
Eutrophication potential	196	0.02	50 %
Abiotic depletion potential for non-fossil resources	196	1.40	62 %
Abiotic depletion potential for fossil resources	196	0.01	77 %
Ozone Depletion Potential	196	0.01	54 %

Discussion of the results



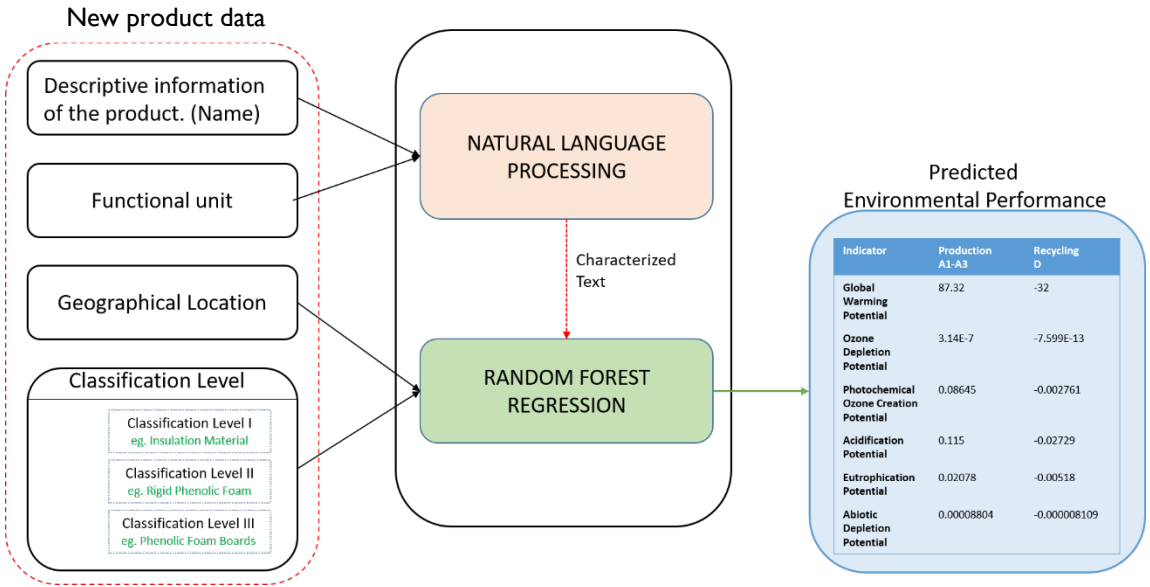


Outliers are a representation of skewed data

Oekobaudat database insufficient for machine learning

Indicators with poor data quality fair poorly in the prediction

Application of the prediction model



Indicator	Production A1-A3	Recycling D
Global Warming Potential	87.32	-32
Ozone Depletion Potential	3.14E-7	-7.599E-13
Photochemical Ozone Creation Potential	0.08645	-0.002761
Acidification Potential	0.115	-0.02729
Eutrophication Potential	0.02078	-0.00518
Abiotic Depletion Potential	0.00008804	-0.000008109

Can predict environmental performance using few input parameters

Applicable for construction products

Not intended to replace traditional LCA but rather a quick prediction

Application of the prediction model

Description

Reinforcement steel wire

Quantification Unit

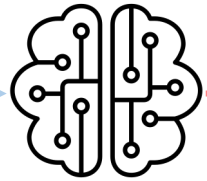
1 Kg

Geographical location

Germany

Classification

- Metals
- Steel and iron
- Steel reinforcement mesh



Ensemble learning

Environmental Impact Indicators	Original Values	Units	Predicted values
Global warming potential (GWP)	0.6834	kg CO2 eq.	0.564
Ozone Depletion Potential (ODP)	2.085E-14	kg R11 eq.	1.272E-14
Photochemical Ozone Creation Potential (POCP)	0.000266	kg Ethene eq.	0. 00019152
Acidification potential (AP)	0.001282	kg SO2 eq.	00071792
Eutrophication potential (EP)	0.0001744	kg Phosphate eq.	0. 000097664
Abiotic depletion potential for non fossil resources (ADPE)	2.302E-7	kg Sb eq.	1.3812E-7
Abiotic depletion potential for fossil resources (ADPF)	7.627	MJ	6.102

Future perspectives

Additional Input Parameters

Name, quantification unit, classification and location are basic information of the product

Additional thermodynamic information that can be provided by the manufacturer could be used as well.

Benchmark ML algorithm

Random forest regression is among the mostly referenced algorithm with good performance

Other algorithms such as KNN, SVM etc., are viable options that could be explored.

Extended Database

Oekobaudat only has 1000 EPD's and was chosen because they are publically available

INIES, France, has the largest database of EPDs worldwide and could be used for the next iteration.

Thank you for your attention!

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