Environmental model using life cycle assessment and artificial intelligence techniques to predict impacts on industrial water treatment.

José de Jesus¹, Karla Oliveira-Esquerre¹, Diego Lima Medeiros¹

¹Federal University of Bahia (UFBA), Growing with Applied Metrics and Mindful Analysis (GAMMA), Industrial Engineering Program (PEI). Professor Aristides Novis Street, 02, Federação, 40210-630, Salvador, Bahia, Brazil. *Corresponding author: jose.oduque@hotmail.com

Abstract. With the advancement of globalization, the growing demand for environmental resources in industrial processes and the increasing availability of data and information, the need to align data modeling concepts with Artificial Intelligence (AI) techniques and existing environmental tools has emerged. From a sustainability perspective, life cycle assessment (LCA) is an extremely important tool in ensuring adequate practices in environmental thinking. It is through the life cycle assessment (LCA) that it is possible to measure the environmental impacts from products and processes, as well as to make projections that minimize these impacts. This research employed an artificial intelligence (AI) methods, namely adaptive neurofuzzy inference system (ANFIS) model, to predict life cycle environmental impacts in industrial water treatment using aluminum sulfate and Tannin-Base biocoagulant. The results show that different AI algorithms are used to build LCA models. The AI algorithms in the studies work from problem identification to the solution stage, so the integration between AI and LCA makes it possible to build predictive machine learning models to enable assertiveness in decision making.

1. Introduction
Currently, the growing environmental problem has been causing the awakening of society's sustainable awareness and providing a greater movement in the effort to ensure harmony between the economy, growth and environmental conservation. In this context, sustainable development plays an extremely important role in the balance between society's productivity demands and the preservation of existing natural resource reserves. From a sustainability perspective, life cycle assessment (LCA) is an extremely important tool in ensuring adequate practices in environmental thinking. It is through life cycle assessment (LCA) that it is possible to measure the environmental impacts from products and processes, as well as to make projections that minimize these impacts, however with the increasing availability of data and information on products and processes, making these systems increasingly complex and automated, you have to consider that there are challenges with regard to the four steps of the LCA (i.e. objective and scope definition, lifecycle inventory, lifecycle impact analysis and interpretation) that must keep up with the trend of application of the tool and find a combination of methods that allows the evaluation and provides a perspective of promising research directions ensuring assertiveness in decision making. The volume of data and information generated daily in
commercial transactions, social networks, analyses, sales and delivery of products, logistical processes, search engines and others, makes the use of Artificial Intelligence systems part of society's daily life. Modern. These systems are able to extract accurate and valuable information, perform tasks, solve problems and make sense of data from their analysis. The use of artificial intelligence systems has contributed to the solution of problems in various areas of society, especially with regard to environmental issues, such as real-time monitoring of devastated areas, studies of the dimension of environmental impacts, mapping of regions affected by ecological disasters, minimization of uncertainties associated with environmental studies, and others. The main advantage of using artificial intelligence systems is that the community needs to have a thorough understanding of the relevant technologies behind modern data science, and it also needs to form a strong vision of what can be done with these new technologies in the future. context of environmental applications. The concepts of Artificial Intelligence (AI), Big Data and Machine Learning, for example, have been worked on by data scientists around the world and transformed many aspects of political, social and economic dimensions. Data scientists argue that emerging data science should be taken as a new paradigm of science and research, and that it still requires a long evolution from empirical observation, theoretical analysis and computer simulations. With this, it is necessary to see data science as a new field for research, taking advantage of all the availability of data with more advanced techniques, of artificial intelligence, to synthesize and examine existing theories and models. Data analysis has always been one of the main mechanisms of scientific investigation, but nowadays, scientists need to lean between the new generation and data analysis, with the classicist methods of existing analysis. Therefore, the main objective of this research is to conduct an evidence-based review, using data mining techniques on the context of Life Cycle Assessment (LCA) and its intersection with artificial intelligence methods in different sectors of society, as well as, understand its main technological and institutional obstacles to the adoption of these technologies in the world scenario.

2. Materials and methods
In this study, the ANFIS method was used to model the production of tannin-based biocoglante, described below in Figure 1 and Table 1, Table 2 and Table 3.

![Figure 1. Two-level ANFIS structure for environmental prediction of water treatment using aluminum sulfate and tannin-based biocoagulant.](image)

Fuzzy logic, as one of AI methods, provides a numeric system and al- lows for simple presentation of production process knowledge by IF- THEN rules (Singh and Gill, 2010). Fuzzy set theory and the associated fuzzy logic are considered a powerful and well-known modeling technique (Zedeh, 1965).
Based on Sugeno fuzzy modeling, natural language is employed for qualitative action of the system (Sugeno and Yasukawa, 1993).

Quantities of energy inputs and outputs in the production of bio-coagulants and use in water treatment.

**Table 1** Gate-to-gate inventory of the production of 1 kg of tannin-based bio-coagulant.

| Materials     | Amount | Unit   | GSD2 |
|---------------|--------|--------|------|
| Acacia Bark   | 29,44  | kg     | 1,07 |
| Water         | 0,87   | m³     | 1,05 |
| Electricity   | 0,63   | kWh    | 1,5  |
| Methanol      | 3,25   | L      | 1,05 |

Source: Own elaboration

*GSD2: square geometric standard deviation.

**Table 2** Foreground inventory for 1 m³ of distributed water.

| Stage          | Amount   | Unit   | GSD2 |
|----------------|----------|--------|------|
| **Uptake**     |          |        |      |
| Chlorine       | 0.030    | kg     | 1,05 |
| Electricity    | 0.54     | kWh    | 1,07 |
| **Treatment**  |          |        |      |
| Aluminum Sulfate| 0.26    | kg     | 1,05 |
| Bio-coagulant  | 0.08     | kg     | 1,05 |
| Sodium Carbonate| 0.12    | kg     | 1,05 |
| Polyelectrolyte| 0.0026   | kg     | 1,05 |
| Electricity    | 0.38     | kWh    | 1,07 |
| Chlorine       | 0.025    | kg     | 1,05 |
| Sludge         | 0.020    | m³     | 1,09 |
| Infrastructure | 3.07E-9  | unit   | 3.28 |
| **Sludge generated** | 0.02  | m³    | 1.05 |

*GSD2: square geometric standard deviation.

**Table 3** Emissions from bio-coagulant production.

| Materials                      | Amount | Unit   | GSD2 |
|--------------------------------|--------|--------|------|
| **Emissions to Air**           |        |        |      |
| Methanol                       | 2,57   | kg     | 1,50 |
| Water                          | 0,23   | kg     | 1,05 |
| Particulate matter             | 0,07   | kg     | 3,00 |
| Total organic carbon           | 0,007  | kg     | 1,05 |
| Organic compounds volatile     | 0,003  | kg     | 1,50 |
| Carbon dioxide, biogenic        | 0,36   | kg     | 1,05 |
| Sulfur dioxide                 | 0,04   | kg     | 1,05 |
| Carbon monoxide                | 0,18   | kg     | 1,05 |
| **Emissions for Treatment**    |        |        |      |
| Residual waters                | 0,8    | m³     | 1,50 |

*GSD2: square geometric standard deviation.
3. Results and Discussion

Figure 2. shows the results of this contribution.

The environmental impact contribution process aims to unify the results obtained from different categories of environmental impacts on the same graph and magnitude. The coagulant that presented the greatest contributions within the human categories was aluminum sulfate, with emphasis on the categories of ecotoxicity and toxicity. In the other categories, observe the environmental performance of aluminum superior to the environmental impacts in relation to the biocoagulant. In this way, the environment remains the toxicity of the human ecotoxicity categories with regard to the life cycle of the use of coagulating agents in the outstanding processes of industrial water treatment. In order to identify an energy demand, water footprint and carbon footprint of the evaluated process, contributions to these categories were also simulated.

Table 4 ANFIS structure to eliminate the environmental impacts of water treatment using aluminum sulfate and tannin-based biocoagulant.

| Category | ANFIS models | Type | Number | Learning method | R² | RMSE | MAPE (%) |
|----------|--------------|------|--------|----------------|----|------|-----------|
| AC       | ANFIS (1) Gbell Linear 5,6 32 Hybrid 0.409 0.652 0.080 | | | | | | |
|          | ANFIS (2) Gbell Linear 5,6 32 Hybrid 0.472 0.633 0.091 | | | | | | |
|          | ANFIS (3) Gbell Linear 5,6 32 Hybrid 0.342 0.679 0.091 | | | | | | |
|          | ANFIS (4) Gbell Linear 5,6 32 Hybrid 0.454 0.528 0.057 | | | | | | |
| TE       | ANFIS (1) Gbell Linear 5,6 32 Hybrid 0.293 0.571 0.018 | | | | | | |
|          | ANFIS (2) Gbell Linear 5,6 32 Hybrid 0.384 0.641 0.087 | | | | | | |
|          | ANFIS (3) Gbell Linear 5,6 32 Hybrid 0.329 0.559 0.082 | | | | | | |
|          | ANFIS (4) Gbell Linear 5,6 32 Hybrid 0.331 0.594 0.056 | | | | | | |
|          | ANFIS (1) Gbell Linear 5,6 32 Hybrid 0.454 0.528 0.057 | | | | | | |
|          | ANFIS (2) Gbell Linear 5,6 32 Hybrid 0.384 0.641 0.087 | | | | | | |
|          | ANFIS (3) Gbell Linear 5,6 32 Hybrid 0.329 0.559 0.082 | | | | | | |
|          | ANFIS (4) Gbell Linear 5,6 32 Hybrid 0.331 0.594 0.056 | | | | | | |
| AE-N     | ANFIS (1) Gbell Linear 5,6 32 Hybrid 0.203 0.606 0.103 | | | | | | |
|          | ANFIS (2) Gbell Linear 5,6 32 Hybrid 0.217 0.651 0.078 | | | | | | |
|          | ANFIS (3) Gbell Linear 5,6 32 Hybrid 0.531 0.582 0.073 | | | | | | |
| AE-P     | ANFIS (1) Gbell Linear 5,6 32 Hybrid 0.599 0.627 0.086 | | | | | | |
|          | ANFIS (2) Gbell Linear 5,6 32 Hybrid 0.599 0.627 0.086 | | | | | | |
|          | ANFIS (3) Gbell Linear 5,6 32 Hybrid 0.599 0.627 0.086 | | | | | | |
| HT-A     | ANFIS (1) Gbell Linear 5,6 32 Hybrid 0.556 0.662 0.089 | | | | | | |
4. Conclusion
In terms of life cycle assessment, these methods were combined and applied in studies aimed at agriculture, climate and engineering studies. The field of application is characterized by algorithms capable of learning from examples and reproducing. Its foundations are based on intensive data analysis and its application in LCA can be seen in solving environmental problems. Being considered efficient and economical substitutes for conventional procedures, these artificial intelligence approaches provide a high level of capability, deal with the complexities of uncertain, interactive and dynamic problems and contribute to the minimization of uncertainties associated with the process.

5. Acknowledgments
The authors are grateful to the Coordination for the Improvement of Higher Education Personnel (CAPES)- Finance Code 001 and Industrial Engineering Graduate Program (PEI) at the Federal University of Bahia (UFBA) for supporting this research.

6. References
[1] Azapagic, A.; Millington, A.; Collett. A. 2006. A methodology for integrating sustainability considerations into process design. Chemical Engineering Research and Design. 84(A6): 439–452.

[2] Froemelt, A., Dürrenmatt, D. J., Hellweg, S. 2018. Using Data Mining To Assess Environmental Impacts of Household Consumption Behaviors. Environmental Science & Technology. 52 (15) 8467-8478.

[3] Hosseinazadeh-Bandbafha H., Nabavi-Pelesaraei A., Majid K; Ghahderijani M., Chau, K. 2018. Application of data envelopment analysis approach for optimization of energy use and reduction of greenhouse gas emission in peanut production of Iran. Journal of Cleaner Production. 172. 1327–1335.

[4] Hosseinazadeh-Bandbafha H., Safarzadeh D., Ahmadi, E. 2019. Combined life cycle assessment and artificial intelligence for prediction of output energy and environmental impacts of sugarcane production. Science of the Total Environment. 664.1005-1019.

[5] Hosseinazadeh-Bandbafha, H., Chau, K. W. 2018. Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production. Science of the Total Environment. 631–632; 1279–1294.

[6] Hosseinazadeh-Bandbafha, H., Safarzadeh, D., Ahmadi E, Nabavi-Pelesaraei, A., Hosseinazadeh-Bandbafha, E. 2016. Applying data envelopment analysis to evaluation of energy efficiency and decreasing of greenhouse gas emissions of fattening farms. Energy. 1-11.

[7] Hou, P., Jolliet O., Zhu, J., Xu, M. 2020. Estimate ecotoxicity characterization factors for chemicals in life cycle assessment using machine learning model. Environment International. 135.

[8] Huntingford, C., Jeffers, E. S., Bonsall, M. B, MChristensen, H., Lees, T., Paramesh, V., Arunachalam, V., Nikkhah, A., Das, B., Yang, H. 2019. Machine learning and artificial intelligence to aid climate change research and preparedness. Environ. Res. Lett. 14.

[9] ISO (INTERNATIONAL ORGANIZATION FOR STANDARDIZATION). 2006 14044: Environmental managements - lifecycleassessments – requirementsandguidelines. InternationalOrganization for Standardization.
[10] Kaab, A., Sharifi, M., Mobli, H., Nabavi-Pelesaraei, A., Chau, K. W. 2019. Use of optimization techniques for energy use efficiency and environmental life cycle assessment modification in sugarcane production. Energy. 181. 1298-1320.