Journal of Ambient Intelligence and Humanized Computing (2023) 14:16867–16878
https://doi.org/10.1007/s12652-023-04702-w

ORIGINAL RESEARCH

Data-driven approaches for sustainable agri-food: coping with sustainability and interpretability

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Received: 7 June 2023 / Accepted: 13 September 2023 / Published online: 5 October 2023

Abstract

Motivated by the increasing interest in machine learning algorithms for data-driven applications in agri-food addressing sustainability issues and by the ongoing discussion on the interpretability and sustainability of such algorithms, we compare congruently the performance of some state-of-the-art techniques and a new version (here proposed for the first time) of Co-Active Neuro-Fuzzy Inference System, equipped with fractional regularization (CANFIS-T for short). To this end, we consider two case studies retrieved from the literature and dealing with two approaches for sustainability development, i.e. ex-ante Life Cycle Assessment and Supply Chain Operations Reference in the agri-food context. Such approaches are set in a data-driven framework and completed by the above-mentioned machine learning techniques. The state-of-the-art techniques from the relevant literature are the ensemble ANFIS, Radial Basis Function Network and Decision Tree. The techniques are compared from the computational, interpretability and energy standpoints. From a formal perspective, we prove what negatively affects the accuracy of ensemble ANFIS. On the basis of the performed experiments, we notice that except for the ensemble ANFIS, all the approaches can be regarded as sustainable, with energy savings over 99%, while only CANFIS-T keeps both good accuracy and interpretability (with up to 4 rules) when the number of input and output variables gets large.

Keywords Fuzzy sets · CANFIS · LCA · SCOR · Energy

1 Introduction

The European Union (EU) is committed to the United Nations (UN) 2030 Agenda and the sustainable development goals (SDGs). In every field, sustainability issues have been prioritized. Typical procedures for sustainability development are Life Cycle Assessment (LCA) and Supply Chain Management (SCM) (Glavic and Lukman 2007).

LCA can be defined as "the method/process for evaluating the effects that a product has on the environment over the entire period of its life, thereby increasing resource use efficiency and decreasing liabilities" (Glavic and Lukman 2007). Most LCA studies in scientific literature and industrial practice are applied ex-post for comparing production systems in well-defined case studies or to prove compliance with environmental guidelines and green certificates. Anyway, determining possible environmental impacts at an early stage of research and development allows reorienting the development activities towards improved environmental performance levels at relatively low costs. This has motivated the use of the ex-ante LCA, even though its output should not be interpreted as an absolute result but rather as an indication of what might happen (Tsalidis and Korevaar 2022).

There are several studies highlighting the usefulness of the ex-ante LCA for identifying environmental issues at an early stage of development, regardless of the product, process, or service, especially for the food and feed sector (Ott et al. 2022). For instance, in Leon (2022), ex-ante LCA

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was performed to evaluate the potential changes in fertilizer application rates and life cycle greenhouse gas emissions when dealing with biological nitrification inhibition-enabled wheat. Already popular in several fields, machine learning (ML) techniques have also been proven to be useful to complement LCA for a better interpretation of the results (Prioux et al. 2022). A first concrete attempt to formalize an ML framework for ex-ante LCA was presented in Karka et al. (2022), where Radial Basis Function networks (RBFN) and Decision Trees (DTs) were used to predict single LCA indicators in the context of bio-based processes. In Ghasemi-Mobtaker et al. (2022), given the typical process inputs for the LCA analysis of wheat production, the global warming potential (GWP) was predicted by using a sequence of Adaptive Neuro-Fuzzy Systems (ANFIS), called ensemble ANFIS (e-ANFIS). It must be pointed out that this e-ANFIS is a serial-like scheme, different from the ensemble of ANFIS proposed in Melin et al. (2012), which is a parallel-like scheme, where the results of each ANFIS are integrated by direct average and weighted average to give the outcome of the computing scheme. Yet, the idea behind e-ANFIS is somewhat different from the ensemble approach using different ML techniques (e.g. see Saggi et al. 2022).

Regarding SCM, it can be defined as "a process of planning, implementing and controlling the operations of the supply chain (SC) with the purpose of satisfying consumer requirements" (Glavic and Lukman 2007). There are numerous studies focusing on SCs in agri-food (e.g. see D'Arienzo and Ritá 2020; de Falco et al. 2018; Morella et al. 2021). The supply chain operations reference (SCOR) model can be regarded as a diagnostic tool for assessing the SC processes (Huan et al. 2004). Over the last years, the SCOR model has become very popular, with several applications also in the agri-food sector (Ntabe et al. 2015). This method has five scopes, namely: plan, source, make, deliver, and return. Additionally, five dimensions are considered, i.e. reliability, responsiveness, flexibility, cost, and asset. These criteria are expanded hierarchically in order to identify gaps and improvement opportunities for the high-level criteria starting with low-level criteria. Due to the growing interest in sustainability (especially environmental issues), recent versions of SCOR have been equipped with greenness criteria. These criteria include carbon emission, liquid waste generated, air pollutant emission, solid waste generated, and recycled waste. Anyway, as emphasized in Stohler et al. (2018), the integration of sustainability metrics into SCOR process models is underway. It must be pointed out that the SCOR model itself is not able to adapt proactively to any changes in the system (Lima-Junior and Carpinetti 2019). Enabling techniques in this regard are from the realm of Artificial Intelligence (AI). For instance, in Lima-Junior and Carpinetti (2019, 2020), the performance metrics proposed by the SCOR model are combined with AI techniques in order to have predictive evaluation systems. Similar ideas are exploited in Khan et al. (2023), but covering sustainability.

Digital technologies, particularly artificial intelligence (AI), play a central role in attaining the SDGs (Vinuesa 2020). Recently, the discussion has focused on sustainable AI. Sustainable AI can be understood in two ways: AI for sustainability and sustainability of AI (van Wynsberghe 2021). There is a growing number of publications dealing with AI for the SDGs (Vinuesa 2020). Considering the increasing importance of AI, the environmental impact of AI systems also needs to be duly considered. Only very little research has been performed addressing the environmental cost of AI (van Wynsberghe 2021; Ferro et al. 2021). It has been shown that the training and tuning of a complex architecture using deep learning produced the same amount of carbon dioxide as five cars during their lifespan (see Ferro et al. 2021 and references therein). Most machine learning (ML) algorithms are costly to train and develop, both from the computational and energy standpoint. Thus, AI is rapidly becoming economically, technically, and environmentally unsustainable. Some efforts have been exerted to study the energy consumption of a class of ML algorithms, i.e. that of DTs (Ferro et al. 2021). On the other hand, AI is expected to be human-centred, and in such a vision, any algorithm should be not only sustainable but also interpretable (Auernhammer 2020). Interpretable approaches may be regarded as humanly understandable with regard to the interactions in the modelling process. The interpretability should be addressed every time the modelled phenomena have socioeconomic implications, to allow different stakeholders to understand algorithmic decisions, in agreement with current regulations (Regulation 2016).

In this paper, we consider two case studies dealing with two approaches for sustainability development, i.e. ex-ante LCA and SCOR, both enhanced by AI. The first case is retrieved from Ghasemi-Mobtaker et al. (2022) and the second one from Lima-Junior and Carpinetti (2020). Both in Ghasemi-Mobtaker et al. (2022); Lima-Junior and Carpinetti (2020), the e-ANFIS was used. We formally prove in this paper that the error affecting the final output in e-ANFIS is amplified through the partial outputs of such a computing scheme, discussing the order of this error. We introduce a new version of Co-Active Neuro-Fuzzy Inference System (CANFIS), equipped with fractional regularization, named CANFIS-T. We compare this approach against those in the relevant literature, i.e. e-ANFIS, due to several applications in agri-food, RBFN and DTs, used for ex-ante LCA as discussed in Karka et al. (2022), in addition to the fact that the latter was considered as a sustainable approach (Ferro et al. 2021). The numerical experiments on the two case studies come after a brief preliminary study to start checking the performance of the considered approaches. Accuracy, interpretability and sustainability of all the approaches are discussed.

This paper is structured as follows. In the next section, the related works are briefly presented. In Sect. 3, the proposed CANFIS-T is introduced, and the other approaches used for comparative purposes, i.e. e-ANFIS, RBFN and DTs, are briefly recalled. Section 4 is devoted to numerical experiments. Finally, in the last section, some conclusions are drawn.

2 Related works

The role of AI in sustainable agri-food has been widely discussed (Sharma 2021). AI is deemed to offer the means to tackle all food and agriculture-related problems. Intelligent systems, decision-making strategies, robust forecasting techniques may all contribute to increased efficiency, reduced resource consumption, and cost. The value of AI in agri-food is expected to grow rapidly with a rate of over 22% (Sharma 2021). While in the recent review (Sharma 2021) fuzzy logic (FL) was mentioned among the others as participating in the AI revolution of the agri-food sector, not many details were discussed about the FL techniques. Among the FL approaches, CANFIS and e-ANFIS must be considered because of their application in agri-food, as already mentioned in the previous section and as will be better discussed in this section.

In many papers (e.g. see Abyaneh 2016-Gholami 2023), CANFIS was improperly used as a multi-input single-output system. i.e. as ANFIS. CANFIS was used to predict the soil temperature in Abyaneh (2016); Talaee (2014). In Aytek (2009); Tabari et al. (2012); Malik and Kumar (2015), CANFIS was utilized to estimate evapotranspiration or pan evaporation, showing its robustness in comparison with other models. In Malik et al. (2017), CANFIS was used to predict the daily suspended sediment concentration in an Indian river. CANFIS outperformed ANN and multiple linear and nonlinear regressions. In Gholami (2023), CANFIS was used to model the relationships between runoff and factors such as rainfall, antecedent soil moisture, soil texture, forest cover, and percentage of litter cover.

A proper application of CANFIS, with three inputs and two outputs, can be found in Gonzalez Perea et al. (2021), where it was used to forecast one-day ahead distribution in energy tariff periods of the irrigation depths at the farm level. The tuning of the CANFIS model was obtained by NSGA-II. Three models were obtained, namely for rice, tomato, and maize. Another proper application of CANFIS can be found in Bayatvarkeshi (2021), where it was used to predict the soil temperature at six different depths after having pre-processed the data by using wavelets.

Over the last few years, e-ANFIS has been appearing in several works in the agri-food area. Some of them deal with LCA. For instance, in Mousavi-Avval (2017), an e-ANFIS was used to predict output energy, economic productivity and environmental emissions of canola production, complementing the LCA analysis for the environmental profile of canola production. Similarly, in Nabavi-Pelesaraei et al. (2019), the LCA was complemented by an e-ANFIS to predict economic profit, output energy and global warning in milling factories. In Khoshnevisan et al. (2014), e-ANFIS was used to predict the environmental indices of greenhouse production of tomatoes and cucumbers. The authors used Life Cycle Inventory (LCI) data as inputs to predict energy indices in greenhouse production. A similar contribution is offered in Kaab (2019), where the application is sugarcane production. Sugarcane is also the topic of Yani (2022), but the authors did not use LCI data as input for the e-ANFIS; they used different indicators from the relevant literature to assess the sustainability of the sugarcane SC.

In Chen et al. (2020), the authors employed an e-ANFIS for maximum yield prediction given inputs from different sensor nodes such as humidity, soil moisture, and temperature, in addition to other information on the crops. Finally, in Mardani et al. (2019), an e-ANFIS was designed to predict carbon dioxide emissions, given some indicators.

In all the articles cited in this section, the sustainability of AI was not considered. Sustainable AI, also called green AI, has been attracting growing interest, especially over the last three years (Verdecchia et al. 2023). The recent review (Verdecchia et al. 2023) shows that green AI is mostly tackled at the level of energy efficiency. In this respect, DTs seem to be more energy efficient and with minimal impact on accuracy than other considered approaches (Verdecchia et al. 2023). According to the same review, and to the best of our knowledge, e-ANFIS and CANFIS have not been explored yet from the sustainability perspective. In addition to the above-mentioned DTs, RBFNs must be considered for comparison purposes because appearing in the relevant literature (Sharma 2021; Karka et al. 2022). Finally, since green AI should also be transparent (Osifo 2023), and transparency is a feature of interpretability (Lipton 2018), the above-mentioned approaches should also be checked for interpretability. These are the research gaps that will be covered in this paper.

3 The approaches

In this section, we describe the proposed approach and briefly recall the state-of-the-art approaches, i.e. the approaches we refer to for a fair comparison. The considered state-of-the-art approaches are e-ANFIS, RBFN and DTs.

3.1 The proposed approach: CANFIS-T

The Co-Active Neuro-Fuzzy Inference System (CANFIS) is a generalization of the Adaptive Neuro-Fuzzy Inference System (ANFIS) (Mizutani and Jang 1995). Like ANFIS (Jang 1993), it presents a multi-layered network architecture to describe the Takagi-Sugeno fuzzy inference system, but unlike ANFIS, it allows for multiple outputs. Hence, while ANFIS models Multi-Input-Single-Output (MISO) systems, CANFIS models Multi-Input-Multiple-Output (MIMO) systems. In CANFIS, the fuzzy rules are constructed with shared membership values to take into account any possible correlation among outputs.

Let $\mathbf{x} = \{x_1, \dots, x_n\}$ be the input vector with n attributes. Let L_i denote the ith layer of this network. The operations performed through the different layers can be summarized as follows:

- $L1, \quad u_{ir} = \mu_{A_{ir}}(x_i),$
- $L2, \quad w_r = \Pi_{i=1}^{n} u_{ir},$
- $L3, \quad f_{rk} = w_r C_{rk}(\mathbf{x}),$
- $L4, \quad \bar{o}_k = \sum_{r=1}^{R} f_{rk},$
- $L5, \quad o_k = \bar{o}_k \left(\sum_{j=1}^{R} w_j \right)^{-1},$

where $A_{ir}, i = 1, 2, \dots, n$, are fuzzy sets representing linguistic attributes of the input x_i in the r-th rule ($r = 1, 2, \dots, R$), and o_k, with $k = 1, \dots, p$, are the p computed outputs. The linear functions $C_{rk}(\mathbf{x})$ are a linear combination of x_i through $nRp \times p$ unknown parameters. The fuzzy sets are uniquely identified by means of membership functions (MFs), here assumed to be parameterized functions such as the Gaussian function:

$$\mu_{A_{ir}}(x) = \exp\left(-\left(\frac{x_i - \bar{c}_{ir}}{\bar{a}_{ir}} \right)^2 \right), \tag{1}$$

where $\bar{a}_{ir}, \bar{c}_{ir}$ are the function's parameters.

A CANFIS scheme is depicted in Fig. 1. Like ANFIS, the standard CANFIS uses a hybrid learning approach, including backpropagation and least-squares (LS) method.

Given N training samples, the following matrix equation is obtained using the training data:

$$\mathbf{H\Theta} = \mathbf{O}, \tag{2}$$

where $\mathbf{O}$ is the $N \times p$ output matrix, $\mathbf{\Theta}$ is the matrix of the unknown parameters, $\mathbf{H} = [\overline{\mathbf{H}}_1 \dots, \overline{\mathbf{H}}_p]$ is the block matrix consisting of $N \times nR$ matrices $\overline{\mathbf{H}}_i, i = 1, \dots, p$.

The LS method is formulated as

$$\min_{\theta} \|\mathbf{H\Theta} - \mathbf{O}\|^2 \tag{3}$$

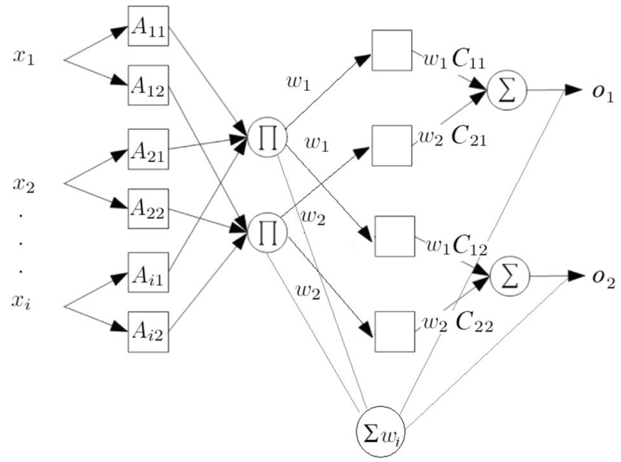

Fig. 1 A CANFIS architecture

with the solution

$$\mathbf{\Theta}^* = \mathbf{H}^*\mathbf{O}, \tag{4}$$

where $\mathbf{H}^* = (\mathbf{H}^T\mathbf{H})^{-1}\mathbf{H}^T$ is the pseudoinverse of $\mathbf{H}$. The fractional Tikhonov method represents a generalization of the standard LS method through the following minimization problem

$$\min_{\Theta} \|\mathbf{H\Theta} - \mathbf{O}\|_P^2 + \lambda\|\mathbf{\Theta}\|^2, \tag{5}$$

where $\|\Theta\|_P = (\Theta^T \mathbf{P} \Theta)^{\frac{1}{2}}$ and $\mathbf{P}$ is a symmetric positive semi-definite matrix defined as

$$\mathbf{P} = (\mathbf{H}^T\mathbf{H})^{\frac{\alpha-1}{2}}, \tag{6}$$

where $\alpha \in (0, 1)$ is the fractional regularization parameter and λ a general regularization parameter.

Following Tomasiello et al. (2022), the solution is:

$$\Theta^* = (\mathbf{M}^{\frac{\alpha+1}{2}} + \lambda\mathbf{I})^{-1}\mathbf{M}^{\frac{\alpha-1}{2}}\mathbf{H}^T\mathbf{O}, \tag{7}$$

where $\mathbf{M} = \mathbf{H}^T\mathbf{H}$.

In Tomasiello et al. (2022), the accuracy of ANFIS with fractional regularization was formally proved. It is possible to mimic the same proofs to prove the accuracy in the case of multiple outputs in CANFIS.

The jth rule that is possible to extract from CANFIS is

$$\text{IF } x_1 \text{ is } A_{1j} \dots \text{ AND } x_n \text{ is } A_{nj} \text{ THEN } \{C_{j1}, \dots, C_{jp}\}.$$

It is worth mentioning that in order to ensure interpretability in fuzzy systems, there should be a small number of rules allowing easy reading and understanding. This also means that the number of terms should be small enough (e.g. 3–5) (Mencar 2013). This has motivated the adoption of fractional regularization in ANFIS first (Tomasiello et al. 2022) and then in CANFIS.

3.2 Ensemble ANFIS

An ensemble ANFIS (e-ANFIS) model combines multiple individual ANFIS models, each trained with a different set of training data. The output of each model is passed to another ANFIS to make a final prediction. This approach may be an option to model MIMO systems, but clearly, it may be computationally costly. The interpretability is also negatively affected. An example of e-ANFIS is depicted in Fig. 2.

From a formal perspective, this implies the fuzzification of the q intermediate outputs o_i^I by means of the fuzzy sets B_{ir} represented by their membership functions $\mu_{B_{ir}}$, i.e. the final output o^F can be written as:

$$o^F = \frac{\sum_{r=1}^{R} \Pi_{i=1}^{q} \mu_{B_{ir}}(o_i^I) f_r(\mathbf{o}^I)}{\sum_{r=1}^{R} \Pi_{i=1}^{q} \mu_{B_{ir}}(o_i^I)}, \tag{8}$$

where $f_r(\mathbf{o}^I)$ represents the linear combination of the intermediate outputs o_i^I by the unknowns β_i for the rth rule.

A drawback of this approach is that the error affecting the computed intermediate outputs is propagated, also affecting the final output. This is clearly shown by Lemma 1.

Let o_i^I and $\overline{o}_i^I$ be the ith computed and exact output, respectively. Similarly, let o^F and $\overline{o}^F$ be the computed final output and the target. Besides, let $\epsilon_i = |\overline{o}_i^I - o_i^I|$ be the error affecting the ith computed output, with $i = 1, \dots, q$. We prove the following (proof in Appendix).

Lemma 1 *Suppose the membership functions $\mu_{B_{ir}}$ are Lipschitz continuous for any $i = 1, \dots, q$ and $r = 1, \dots, R$. Then it is*

$$e^F = |o^F - \overline{o}^F| = O(\left(\frac{LM+1}{Lm+1}\right)^q), \tag{9}$$

where L is the Lipschitz constant, $M = \max_i \epsilon_i$, $m = \min_i \epsilon_i$.

It is worth recalling that the membership functions usually adopted in the ANFIS schemes, i.e. the Gaussian and the generalized bell-shaped function, are Lipschitz continuous. Lemma 1 clearly shows that the error affecting the final output depends on the errors affecting the intermediate outputs. It provides the order of accuracy of this computing scheme.

3.3 Radial basis function networks

The RBFN is a kind of shallow network consisting of only three layers:

- input layer, which consists of n nodes, given the input vector $\mathbf{x} = \{x_1, \dots, x_n\}$;
- hidden layer, where each hidden node is described by a radial basis function

$$\phi_j(\mathbf{x}) = \phi(\|\mathbf{x} - \mathbf{c}_j\|), \qquad j = 1, \dots K, \tag{10}$$

  where $\mathbf{c}_j$ defines the centre of the unit; there are no weights associated with the connections from the input nodes to the hidden nodes;
- output layer, which is equipped with a linear function; assuming that the output layer consists of a single unit, then it is characterized by a K-dimensional weight vector $\mathbf{w}$, that is

$$y(\mathbf{x}) = \sum_{i=1}^{K} w_i \phi_i(\mathbf{x}), \quad o\ r \quad y(\mathbf{x}) = \frac{\sum_{i=1}^{K} w_i \phi_i(\mathbf{x})}{\sum_{i=1}^{K} \phi_i(\mathbf{x})}. \tag{11}$$

The parameters of the hidden units are computed in an unsupervised manner. A clustering technique, such as K-means, is usually adopted. The learning process consists of two phases: unsupervised tuning of all the parameters in the hidden layer of the network and supervised learning of the weights in the output layer, e.g. by using the recursive least squares approach (Haykin 2009).

Although a multi-output version has been presented in Dua et al. (2010), in order to extract IF-THEN rules from this computing scheme as discussed in Jin and Sendhoff (2003), parallel single-output RBF networks, with the same input nodes, can be adopted.

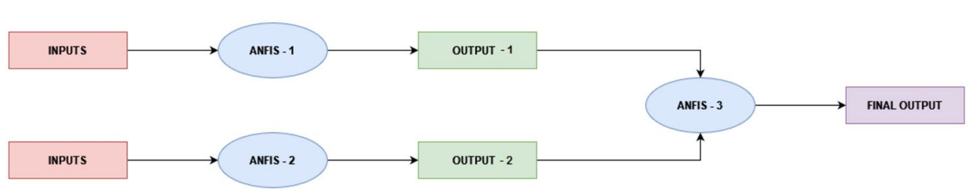

Fig. 2 An e-ANFIS scheme

3.4 Decision trees

Decision trees fall in the class of non-parametric supervised learning algorithms (Breiman et al. 1984). These computing schemes have a hierarchical, tree structure, consisting of a root node, branches, internal nodes (decision nodes) and leaf nodes. The leaf nodes represent all the possible outcomes within the given data. A DT can also be regarded as a set of IF-THEN rules. This also implies that DTs are well interpretable if their depth (i.e. the number of levels) is limited (Molnar 2020). Their depth may influence the accuracy, even though it is not for granted that a deeper tree produces better accuracy. Moreover, a larger number of levels may negatively affect the runtime. Choosing a proper node-splitting function is critical to accuracy improvement. There are several techniques for a better DTs' performance (e.g. see Barros 2012). The consistency, as part of the convergence, of DTs has been widely discussed in the literature (e.g. see Breiman et al. 1984).

The multi-output case is handled by storing all the p output values in leaves, instead of 1, and splitting by computing the average reduction across all the p outputs.

4 Numerical experiments

In this section, we detail the performed numerical experiments.

The original data was generated in the average and standard deviation specified for the two case studies and then it was normalized using min-max normalization in the range [0, 1].

In all the experiments, we used 2-fold cross-validation, even though no cross-validation was used in the main references. Using at least 2-fold cross-validation allows for avoiding biased results due to the choice of the test data.

Regarding CANFIS-T, several values of the regularization parameters were used, i.e. $\alpha \in \{0.1, 0.2, \ldots, 0.9, 1\}$ and $\lambda \in \{10^{-3}, 10^{-2}, \ldots, 10^{2}, 10^{3}\}$. For CANFIS-T, e-ANFIS, and RBFN, the Gaussian function was adopted. The generalized bell-shaped function has also been tried, but it did not bring any significant improvements in the results despite its additional parameter, worsening the computational cost. The numerical experiments were performed using an Intel Core-i5 processor clocking at 1.2 GHz, with the Scilab environment for CANFIS-T, and Matlab for all the other approaches.

As an accuracy measure, we considered the RMSE. The computational effort was measured by the training time. The sustainability of the approaches was measured by the energy consumption (EC) (Ferro et al. 2021; Pereira 2017; Henderson 2020). The energy value is here assumed as the sum of CPU and DRAM energy consumption (Pereira 2017). A common misconception when dealing with EC in software is that reducing the execution time of a program would bring the same amount of energy saving. The energy measured in joules (J) is the total power (watts) consumed during an interval of time (s). Hence, it may sound reasonable a reduction of the consumed energy when reducing time. Anyway, the power cannot be assumed as a constant, and it also has an impact on the energy. Therefore, conclusions regarding this issue may often diverge, as observed in Pereira (2017). To simulate the energy consumption, we used Intel Power Gadget 3.6.

Table 1 Preliminary study, first dataset

Approach	Rules	RMSE	Training time (s)	Energy (J)
CANFIS-T ($\lambda = 1$, $\alpha = 0.9$)	3	0.2914 ± 0.00141	0.48	6.384
e-ANFIS	10	0.57853 ± 0.00989	168.23	2115.221
DT	6	0.2934 ± 0.00211	0.63	8.410
RBFN	20	0.59176 ± 0.11623	0.24	3.112

Cross-validated test results

Table 2 Preliminary study, second dataset

Approach	Rules	RMSE	Training time (s)	Energy (J)
CANFIS-T ($\lambda = 10$, $\alpha = 0.9$)	3	0.29078 ± 0.00043	1.14	11.742
e-ANFIS	85	0.69976 ± 0.00835	1995.26	21,947.863
DT	18	0.2909 ± 0.00165	1.59	19.668
RBFN	45	0.60209 ± 0.02784	0.85	11.22

Cross-validated test results

4.1 Preliminary study

In the preliminary study, we use synthetic data, randomly generated in the range [0, 1]. There are two generated datasets, each one consisting of 2000 samples, but the first one has 11 attributes and 3 targets, while the second one has 19 attributes and 9 targets. These preliminary experiments represent a first attempt to see how the accuracy and the complexity of the considered approaches change when the number of attributes and targets increases. The e-ANFIS scheme for the first dataset is like the one in Fig. 2, i.e. a combination of 3 ANFIS models, where ANFIS-1 has 6 input variables, and ANFIS-2 has 5 input variables. Regarding the second dataset there are two e-ANFIS schemes like the one in Fig. 2, where ANFIS-1/1 and ANFIS-2/1 in the first scheme have both 5 input nodes and ANFIS-1/2 and ANFIS-2/2 in the second scheme have 5 and 4 input nodes respectively.

The results related to the first and second datasets are reported in Tables 1 and 2, respectively. As one can see, the accuracy of CANFIS-T and DT is almost the same, even though the number of rules which can be extracted from CANFIS-T is smaller. This is, in particular, more evident for the second dataset. The shortest training time is offered by the RBFN, though its accuracy is not that good. Regarding energy consumption, this is quite limited for all the approaches except for e-ANFIS. The worst results from any perspective are by e-ANFIS.

It must be mentioned that in both datasets, there is no correlation, i.e. the largest entry of the correlation matrix in both cases was of the order of 10^{-2}. To introduce some correlation in the output data, the second dataset is modified by means of the last column as a sum of the two previous ones. This is shown in Fig. 3, where for the modified data (Fig. 3b), some dark cells (representing entries close to 1) are visible. No significant changes are reported after running the experiments with this modified dataset: all the observed changes are less than 10% on average.

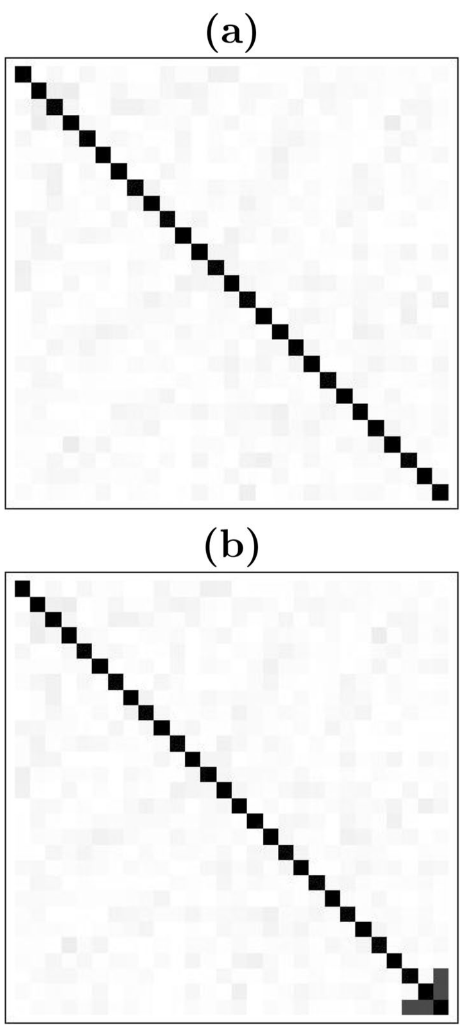

Fig. 3 Preliminary study, second dataset, correlation matrix plot: **a** original data, **b** modified data

4.2 First case study

The first case study is inspired by Ghasemi-Mobtaker et al. (2022), where e-ANFIS was used to predict the GWP indicator, pursuing an ex-ante LCA of wheat production. It is useful recalling that the methodology for ex-ante LCA of any process originates from the idea that previous knowledge of the process can be used to estimate LCA indicators at an early stage of the process development. In a data-driven framework, first, one has to prepare the input–output flows of the model based on prior knowledge. Prior knowledge may come from the literature and implies the selection of a proper set of predictors ad corresponding LCA indicators to create input–output samples. The dataset so formed is then used by a suitable machine learning approach (Karka et al. 2022).

Regarding the dataset used herein, it presents attributes, which, with their average, and standard deviation, have been retrieved from Ghasemi-Mobtaker et al. (2022). They are listed in Table 3. The dataset consists of 5000 samples. There is no correlation among data, with the largest entry of the correlation matrix of order 10^{-2}. The e-ANFIS adopted in our experiments follows the scheme depicted in Fig. 2. More precisely, the inputs to ANFIS-1 are x_1, x_2, x_3, x_4, with y_1 as output. The inputs to ANFIS-2 are x_5, x_6, x_7, with y_2 as output. Finally, y_1 and y_2 are provided as inputs to ANFIS-3, with y_3 as the final output. The obtained results are reported in Table 4, showing the cumulative average RMSE, and in

Table 3 Input and output variables (x_i and y_j respectively, with $i = 1, \dots, 7$ and $j = 1, 2, 3$)

Variable	Description	Average	Standard deviation
x_1	Field operations	1373.75	215.62
x_2	Transport	5726.73	750.37
x_3	Nitrogen	5851.63	2528.76
x_4	Phosphate	1001.86	433.82
x_5	Manure	624.00	653.85
x_6	Biocides	285.12	80.10
x_7	Medium voltage	23,534.59	6646.94
y_1	Wheat grain	77,723.80	14,376.67
y_2	Wheat straw	39,683.33	9401.63
y_3	GWP	624.29	129.93

The unit for GWP is kg CO_2. The unit for the rest of the attributes is MJ ha^{-1}

Table 4 First case study

Approach	Rules	RMSE	Training time (s)
CANFIS-T ($\lambda = 0.01$, $\alpha = 0.9$)	2	0.13733 ± 0.00122	0.98
e-ANFIS	5	0.2546 ± 0.00734	173.22
DT	6	0.1372 ± 0.00212	1.41
RBFN	9	0.5116 ± 0.04231	0.89

Cross-validated test results

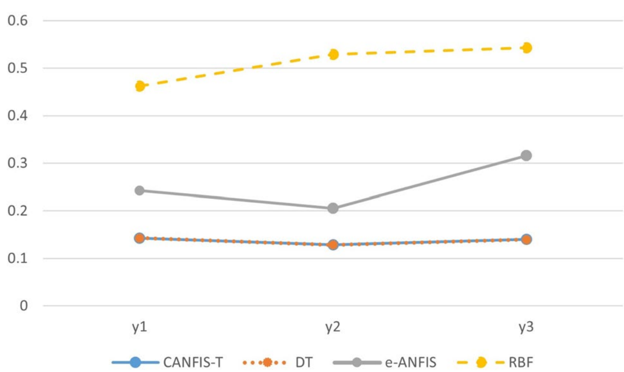

Fig. 4 First case study. Cross-validated test results per output variable

Fig. 4, showing the RMSE for each output variable. The average energy consumption is shown in Fig. 6a. From the results, it is clear that the RBFN and e-ANFIS performed worst. CANFIS-T and DT have similar performance in terms of accuracy. By looking at the training time and consumed energy during the training, CANFIS-T performs slightly better than DT. The training time of the RBFN is similar, though slightly shorter than the one for CANFIS-T. The energy consumption for the RBFN is smaller than that of CANFIS-T but greater than that of the DT. The number of rules of CANFIS-T is only 2, while it is 5 for e-ANFIS, 6 and 9 for the DT and RBFN, respectively. Hence, all the approaches turns out to be interpretable.

4.3 Second case study

The second case study is an adaptation of the study on SCs' performance reported in Lima-Junior and Carpinetti (2020), based on ML and SCOR. In the latter, seven ANFIS schemes were used to model the causal relationships defined by SCOR, to estimate the values of level-1 metrics on the basis of level-2 metrics. The aim of that model was to support a predictive diagnosis to identify which level-1 metric(s) underperform and, consequently, take action. Hence, the inputs were given by level-2 metrics, whereas the output variables represented level-1 metrics. The authors used synthetic data by following (Lima-Junior and Carpinetti 2019). The data referred to a generic SC. Herein, we are considering the same inputs and outputs. Additionally, in order to take into account sustainability, we add to the outputs the CO2 emissions. These have been obtained synthetically based on two facts. First, the CO2 emissions X_{CO2} can be assumed directly proportional to the energy E, i.e. $X_{CO2} = 0.785E$ (He 2019). Secondly, the energy intensities

Table 5 Input and output variables (x_i and y_j respectively, with $i = 1, \dots, 30$ and $j = 1, \dots, 8$); the ndash stands for dimensionless

Variable	Description	Range	Unit
x_1	Orders delivered in full	[0, 1]	–
x_2	Delivery performance	[0, 1]	–
x_3	Documentation accuracy	[0, 1]	–
x_4	Perfect condition	[0, 1]	–
x_5	Value at risk (plan)	$[10, 100]\times10^3$	\$
x_6	Value at risk (source)	$[50, 200]\times10^3$	\$
x_7	Value at risk (make)	$[50, 300]\times10^3$	\$
x_8	Value at risk (deliver)	$[20, 200]\times10^3$	\$
x_9	Value at risk (return)	$[20, 200]\times10^3$	\$
x_{10}	Source cycle time	[1, 6]	Days
x_{11}	Make cycle time	[1, 7]	Days
x_{12}	Delivery cycle time	[1, 7]	Days
x_{13}	Delivery retail cycle time	[7, 20]	Days
x_{14}	Sourcing cost	$[140, 300]\times10^3$	\$
x_{15}	Planning cost	$[25, 50]\times10^3$	\$
x_{16}	Material landed cost	$[70, 150]\times10^3$	\$
x_{17}	Production cost	$[150, 380]\times10^3$	\$
x_{18}	Order management cost	$[220, 480]\times10^3$	\$
x_{19}	Fulfilment cost	$[45, 70]\times10^3$	\$
x_{20}	Returns cost	$[50, 200]\times10^3$	\$
x_{21}	Cost of goods sold	$[1.3, 1.9]\times10^6$	\$
x_{22}	Inventory	$[0.1, 2]\times10^6$	\$
x_{23}	Accounts receivable	$[0.5, 2]\times10^6$	\$
x_{24}	Accounts payable	$[0.5, 2]\times10^6$	\$
x_{25}	Total cost to serve	$[2, 3.53]\times10^6$	\$
x_{26}	$= y_5$	\$	
x_{27}	Supply chain revenue	$[3.5, 10]\times10^6$	\$
x_{28}	Days sales outstanding	[25, 70]	Days
x_{29}	Inventory days of supply	[27, 80]	Days
x_{30}	Days payable outstanding	[30, 72]	Days
y_1	Perfect order fulfilment	[0, 4]	–
y_2	Overall value at risk	$[0.15, 1]\times10^6$	\$
y_3	Order fulfilment cycle time	[10, 40]	Days
y_4	Total cost to serve	$[2, 3.53]\times10^6$	\$
y_5	Denominator of y_6	$[-1.4, 3.5]\times10^6$	\$
y_6	Return on working capital	[– 15, 100]	%
y_7	Cash-to-cash cycle time	[22, 120]	Days
y_8	CO_2 emissions	[78.5, 314]	–

in the manufacturing sector including beverages, fruits and vegetables, grain products may vary approximately in the range [100,400] (TOE energy consumed) (Rademaekers et al. 2020). All the input and output details are reported in Table 5. The dataset consists of 1000 instances. As in the previous case, there is no correlation among data. The authors in Lima-Junior and Carpinetti (2020) used four single ANFIS and one e-ANFIS. We partially follow their scheme since we consider here an additional output, i.e. the CO2 emissions. The input–output details of our e-ANFIS-based scheme are reported in Table 6. As in Lima-Junior and Carpinetti (2020), each e-ANFIS consists of two parallel ANFIS and a final one as depicted in Fig. 2; they appear in Table 6 as e-ANFIS I/ANFIS-i, and e-ANFIS II/ANFIS-i, with $i = 1, 2, 3$, since in our scheme there are two e-ANFIS models and two single ANFIS models.

Since the output y_5 is a partial output, it is not considered among the outputs of CANFIS-T, RBFN and DT.

The results are shown in Table 7 and Fig. 5. The energy consumed during the training is shown in Fig. 6b. As in the previous case, e-ANFIS performed worst. Accuracy, training time and consumed energy during the training of CANFIS-T and DT are very similar. The accuracy of the RBFN is worse, even though better than the one of e-ANFIS, and its training time is the least one. Its energy consumption is the least one as well, though not significantly distant from the one of CANFIS-T and DT. The number of rules which can be extracted from the RBFN and DT is 35 and 28, respectively, while for CANFIS-T is only 4, implying the better interpretability of CANFIS-T.

5 Conclusions

In this paper, we considered two case studies retrieved from the literature to compare the performance in terms of accuracy, sustainability and interpretability of some state-of-the-art techniques, namely e-ANFIS, RBFN, DT, and the newly proposed CANFIS with fractional regularization. The first case study dealt with ex-ante LCA and the second one with SCOR. Before discussing the numerical experiments and results, we formally proved that e-ANFIS has limited accuracy, because of the propagation of the errors affecting the intermediate outputs.

According to the two considered cases, it has been possible to notice what follows. The performance of e-ANFIS was the worst one in terms of training time and energy consumption in both cases. The energy consumption of all the other approaches was comparable, with CANFIS-T performing slightly better in the first case. The least training time was achieved by the RBFN, though not significantly distant from that of CANFIS-T, especially in the first case. The best accuracy was equally achieved by CANFIS-T and DT in both cases.

Regarding interpretability, in the presence of a small number of input and output variables, such as in the first case study, all the approaches ended up with a limited number of rules (i.e. < 10) and hence all were well interpretable; for a larger number of input and output variables, such as in the second case study, only CANFIS-T could be regarded as well interpretable, with only 4 rules, while the other approaches presented a number of rules not less than 28. In both cases, the number of rules extracted from CANFIS-T was the least one. Similar behaviour of the approaches was observed in the preliminary study.

Table 6 Second case study: inputs and outputs for the e-ANFIS based scheme

Model	Input	Output
ANFIS	x_1, x_2, x_3, x_4	y_1
ANFIS	x_5, x_6, x_7, x_8, x_9	y_2
e-ANFIS I/ANFIS-1	$x_{14}, x_{15}, x_{16}, x_{17}, x_{18}, x_{19}, x_{20}, x_{21}$	$y_4 = x_{25}$
e-ANFIS I/ANFIS-2	x_{22}, x_{23}, x_{24}	$y_5 = x_{26}$
e-ANFIS I/ANFIS-3	x_{25}, x_{26}, x_{27}	y_6
e-ANFIS II/ANFIS-1	$x_{10}, x_{11}, x_{12}, x_{13}$	$y_3 = x_{30}$
e-ANFIS II/ANFIS-2	x_{28}, x_{29}, x_{30}	$y_7 = x_{31}$
e-ANFIS II/ANFIS-3	x_{30}, x_{31}	y_8

Table 7 Second case study

Approach	Rules	RMSE	Training time (s)
CANFIS-T ($\lambda = 1000$, $\alpha = 0.9$)	4	0.31331 ± 0.00343	1.91
e-ANFIS	864	0.8528 ± 0.25348	2295.37
DT	28	0.3129 ± 0.00577	1.8
RBFN	35	0.5805 ± 0.12556	1.05

Cross-validated test results

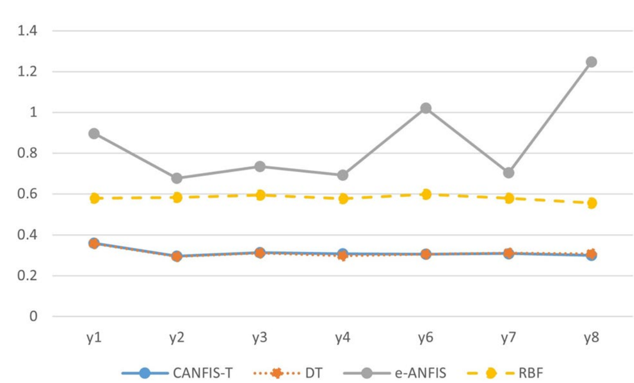

Fig. 5 Second case study. Cross-validated test results per output variable

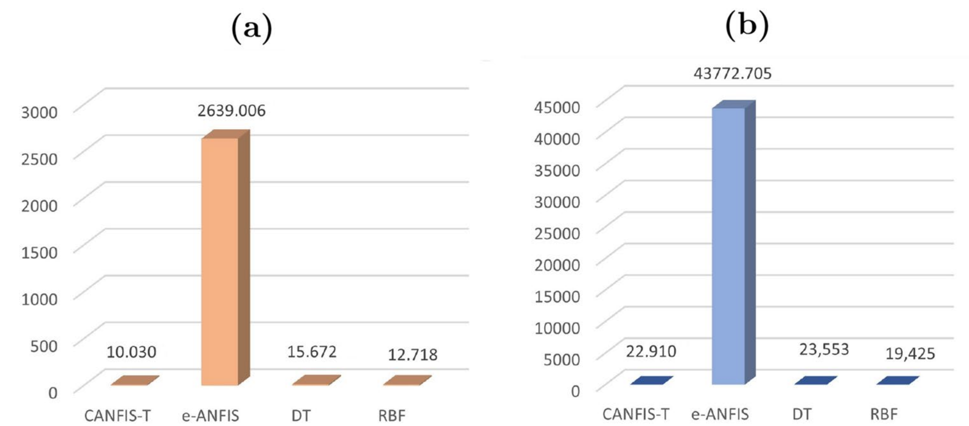

Fig. 6 Energy consumption (J): **a** first case study, **b** second case study

Appendix A: Proof Lemma 1

First of all, let us observe that, because of the hypothesis, it is for any $i = 1, \dots, q$:

$$\mu_{B_{ir}}(o_i^I) = \mu_{B_{ir}}(\overline{o}_i^I + \epsilon_i) \le |\mu_{B_{ir}}(\overline{o}_i^I) - \mu_{B_{ir}}(o_i^I)| + \mu_{B_{ir}}(\overline{o}_i^I) \le L\epsilon_i + \mu_{B_{ir}}(\overline{o}_i^I),$$

where L represents the Lipschitz constant. Besides, since $f_r(.)$ is a linear function in its arguments, it is $f_r(\mathbf{o}^I) = f_r(\overline{\mathbf{o}}^I) + f_r(\boldsymbol{\epsilon})$, where $\boldsymbol{\epsilon}$ is the vector whose ith entry is ϵ_i. Recalling that the highest value taken by the membership functions is 1, it is straightforward to obtain:

$$\begin{aligned}
e^F &\le \left| \frac{\sum_{r=1}^R \Pi_{i=1}^q (L\epsilon_i + \mu_{B_{ir}}(\overline{o}_i^I))(f_r(\overline{\mathbf{o}}^I) + f_r(\boldsymbol{\epsilon}))}{\sum_{r=1}^R \Pi_{i=1}^q L\epsilon_i + \mu_{B_{ir}}(\overline{o}_i^I)} + \right.\\
&\quad \left. - \frac{\sum_{r=1}^R \Pi_{i=1}^q \mu_{B_{ir}}(\overline{o}_i^I) f_r(\overline{\mathbf{o}}^I)}{\sum_{r=1}^R \Pi_{i=1}^q \mu_{B_{ir}}(\overline{o}_i^I)} \right| \\
&\le \left| \frac{\sum_{r=1}^R \Pi_{i=1}^q (L\epsilon_i + 1)(f_r(\overline{\mathbf{o}}^I) + f_r(\boldsymbol{\epsilon}))}{\sum_{r=1}^R \Pi_{i=1}^q L\epsilon_i + 1} + \right.\\
&\quad \left. - \frac{\sum_{r=1}^R \Pi_{i=1}^q \mu_{B_{ir}}(\overline{o}_i^I) f_r(\overline{\mathbf{o}}^I)}{R} \right| \\
&\le \left| \frac{\sum_{r=1}^R (LM+1)^q (f_r(\overline{\mathbf{o}}^I) + f_r(\boldsymbol{\epsilon}))}{R(Lm+1)^q} - \frac{\sum_{r=1}^R f_r(\overline{\mathbf{o}}^I)}{R} \right| \\
&\le \left| \left[\frac{(LM+1)^q}{(Lm+1)^q} - 1 \right] \overline{\mu} \right| + \left| \frac{(LM+1)^q}{(Lm+1)^q} \mu \right| \\
&\le 2 \left| \left(\frac{LM+1}{Lm+1} \right)^q \overline{\mu} \right|
\end{aligned}$$

where $\overline{\mu} = \max_r f_r(\overline{\mathbf{o}}^I)$, $\mu = \max_r f_r(\boldsymbol{\epsilon})$.

The conclusion easily follows. □

Acknowledgements This work has been funded by the European Social Fund via the IT Academy program, the Estonian Research Council, grant PRG1604, and through the funding of SusAn, FACCE ERA-GAS, ICT-AGRI-FOOD and SusCrop ERA-NET.

Funding Open access funding provided by Linköping University.

Data availability Data will be made available on reasonable request.

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