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Fuzzy Logic Model for the Performance Benchmarking of Sugar Plants by considering Best Available Techniques

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Abstract

The paper deals with the problem of performance benchmarking of industrial plants by considering Best Available Techniques (BAT), as determined by the Integrated Pollution Prevention and Control Directive. A Fuzzy Logic Model, based on fuzzy set theory, was constructed for this purpose, in order to compare the performance of plants within a sector's best standards, as expressed in the Reference Document on BAT. The effectiveness of the model was tested in the case study, in which three sugar plants were benchmarked against the BAT.

Keywords

performance benchmarking, fuzzy set theory, IPPC Directive, best available techniques, IPPC permitting process

1. Introduction

Integrated Pollution Prevention and Control (IPPC) Directive [5] strives to achieve a higher level of environmental protection by preventing or reducing the pollution emanating from industrial installations, directly at the source. The authorities throughout Europe are required to issue permits allowing discharge of pollutants into the environment, but these permits must be issued in line with the general principles of the IPPC.

Best available techniques (BAT) are an important element of the IPPC Directive representing techniques with the lowest impact on the environment without compromising the economic performance of industrial plant. The BAT Reference Documents (BREFs) express which techniques can be considered as BAT and provide quantitative BAT benchmarks [1].

To show compliance with the general principles of the IPPC Directive and to meet BAT benchmarks, traditional beet sugar plants (besides many other industrial plants) are urged to establish environmental performance control mechanisms, which would in turn benchmark the results of technological improvements to the achievements defined by BAT.

2. Problem statement

Attempts to benchmark the performance of traditional sugar beet plants are thwarted by problems that are difficult to address by standard mathematical approaches because of the wide range of attributes that have a bearing on assessment. The practical means of benchmarking the performance of sugar plants are still underdeveloped. In spite of many existing frameworks for the sustainability assessment of companies [2, 4], none of them specifically addresses beet sugar plants in providing useful benchmarks to compare the performances of sugar plants with the sector's best standards. For this reason, this paper proposes a Fuzzy Logic Model for the performance benchmarking.

3. Fuzzy Logic Model for the Performance Benchmarking of Traditional Beet Sugar Plants

In the proposed Fuzzy Logic Model (FLM), the intention was to describe each performance indicator of a sugar plant by grading BAT performance levels (i.e. low, medium, high, etc.) according to its value. The model is based on the concepts of fuzzy set theory [9], where no sharp boundaries between performance levels are possible. The model consists of two main components, namely, knowledge base and fuzzy processor, as shown in Fig. 1. Overall plant performance is derived from a group of chosen indicators combined by the **fuzzy rules**, in order to deliver an appropriate sub-index. The fuzzy processing is repeated for each group of indicators. The sub-indices obtained (i.e. sub-indices of raw materials extraction, energy consumption, water consumption and product generation) then represent a new input for a fuzzy processor, in order to finally determine the BAT index (I_{BAT}).

The **knowledge acquisition phase** includes a bibliographical analysis of the existing BAT reference document (BREF) for beet sugar production and related documents in order to determine appropriate indicators and benchmarks for the assessment.

A **linguistic fuzzy set** can express the performance defined by the indicator, using word expressions depending on the value of the indicator. These word expressions indicate the BAT performance level, L_k. In this model, each value of indicator I_i and sub-index I_s, as well as the final I_{BAT}, is categorized into one of the five BAT performance levels, as suggested by Prescott-Allen [6]:

$S(I_i) = S(I_s) = S(I_{\mathrm{BAT}}) = \{L_k$, k = Very Low (VL), Low (L), Medium (M), High (H), Very High (VH)$\}$.

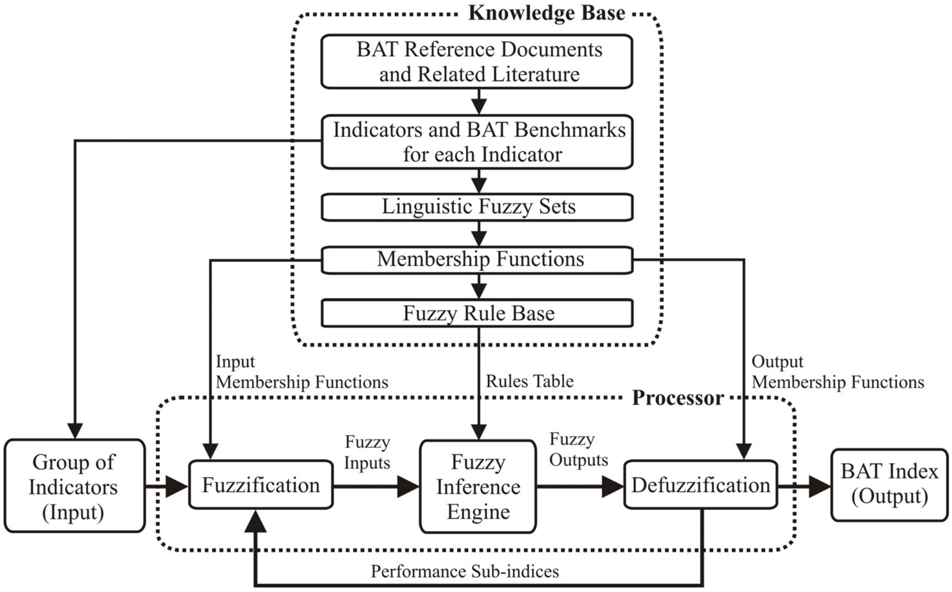

Fig. 1: A schematic representation of the Fuzzy Logic model (FLM).

Each BAT performance level (L_k) is characterized by a **membership function** f_{m} that ranges between 0 and 1. There are many possible types of membership functions, but the proposed model uses triangular or trapezoidal ones due to their simple forms.

The main idea of the FLM is that the indicator value could be a member of more than one BAT performance level. **Fuzzification** determines the degree to which an indicator belongs to each of the appropriate BAT performance levels by means of membership functions, namely, f_{m}: $I_i \rightarrow [0, 1]$ where $I_i \in L_k$. For example, the membership function of the selected indicator $I_{\mathrm{A},0}$ in Fig. 2 is 0.25 for the BAT performance L and 0.75 for the BAT performance level VL.

Once we have fuzzified input indicators with membership function values, they may be combined to the sub-index by the **fuzzy rule base**, which contains a set of IF–THEN rules of the form: IF antecedent THEN consequent, where ‘antecedent’ is an expression composed of the BAT performance levels of one or more indicators connected by fuzzy operators (OR, AND), and ‘consequent’ is an expression that assigns BAT performance level to the output performance sub-index or BAT index. The fuzzy rules IF–THEN are of the following form [3]:

R_n: IF I_1 is $L_{k,1}$ AND I_2 is $L_{k,2}$ AND ... I_i is $L_{k,l}$ THEN I_s is $L_{k,m}$

where R_n is n-th rule, I_i is input indicator, L_k is BAT performance level, I_s is output sub-index, $l = 1, 2, ..., P$, P is the number of input BAT performance levels, $m = 1, 2, ..., M$, M is the number of output BAT performance levels.

The **fuzzy inference engine** combines BAT performance levels, representing the output of each rule to a single fuzzy output. In this paper, Mamdani's type of inference engine was used employing a compositional minimum operator [7]. Let us show the principle of Mandani's type of inference engine, in an example. For the sake of clarity, consider a criterion with three indicators, I_A, I_B and I_C with their membership functions $f_m(I_A)$, $f_m(I_B)$ and $f_m(I_C)$, and a rule base with only two rules for forming sub-index I_s:

Rule #1: IF I_A is Very Low AND I_B is Very Low AND I_C is Very Low THEN I_s is Very Low

Rule #2: IF I_A is Low AND I_B is Low AND I_C is Low THEN I_s is Low

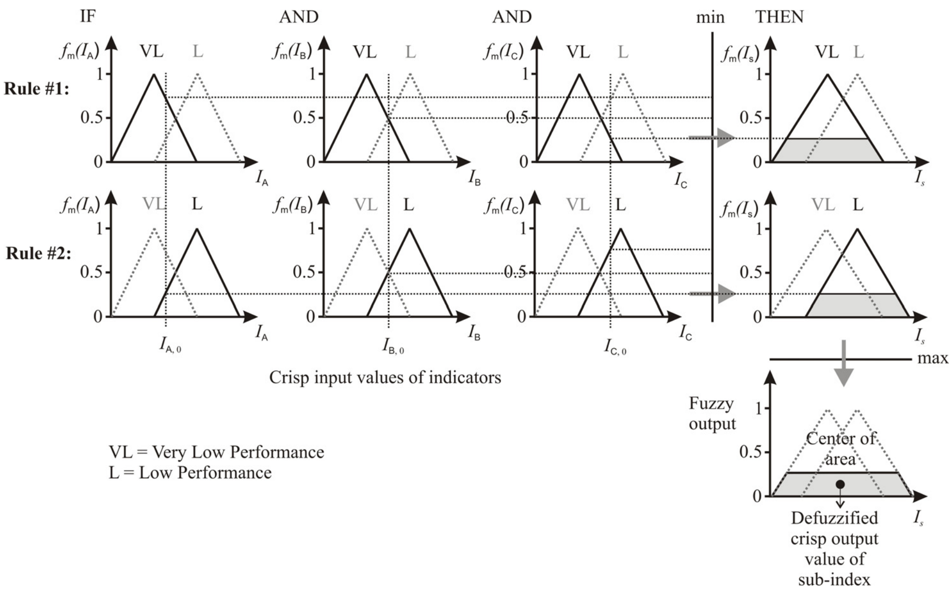

Fig. 2: Example of fuzzy reasoning following the Mamdani's approach.

An estimation of membership function $f_m(I_s)$ for subindex I_s for each rule will be the minimum of the three membership functions of indicators A, B and C (shown by the shaded areas in the third column in Fig. 2).

Rule #1: $f_m\ (I_A) = 0{,}75\ \wedge f_m\ (I_B) = 0{,}50\ \wedge f_m\ (I_C) = 0{,}25 \Rightarrow$ $Min\ \{0{,}75,\ 0{,}50,\ 0{,}25\} = 0{,}25$

Rule #2: f_m $(I_A) = 0{,}25$ $\wedge f_m$ $(I_B) = 0{,}50$ $\wedge f_m$ $(I_C) = 0{,}75$ $\Rightarrow$ *Min* $\{0{,}25, 0{,}50, 0{,}75\} = 0{,}25$

Taking the union of the shaded areas, results in the fuzzy output shown in the third row in Fig. 2.

To translate the fuzzy output into a crisp value, a **deffuzification** is carried out where the crisp value is generated by finding the center of area. A detailed mathematical description of the defuzzification process can be found in Yadav et al. [8].

3.1. Case study

The case study is illustrating the possibilities to adopt the FLM as the benchmarking procedure of a traditional beet sugar plant's environmental performance. The performance of the case-studied beet sugar plant TSO, located in Slovenia, was compared with an imaginative sugar plant having very low performance (Plant VLP), and with a sugar plant which reached BAT Benchmarks by achieving very high performance (Plant VHP).

Twelve basic BAT Indicators (regarding the raw materials, water and energy consumption, products and by-product generation, wastewater release etc.) with determined BAT benchmark values were aggregated into four performance sub-indices for the case-studied plants and finally aggregated into the I_{BAT}.

3.2. Results and discussion

The calculated I_{BAT} revealed that environmental performance efficiencies of plants VLP, VHP, and TSO reached 8.9 %, 90.7 %, and 51.7 % of BAT efficiency, respectively.

The results for performance sub-indices were visualized (Fig. 3). As anticipated, VHP Plant scored high in all the performance aspects, while VLP Plant achieved the lowest scores for sub-indices. The case sugar plant TSO performs well in product/by-product generation. However, extraction of raw materials is the aspect which needs immediate attention. The same is true for energy consumption.

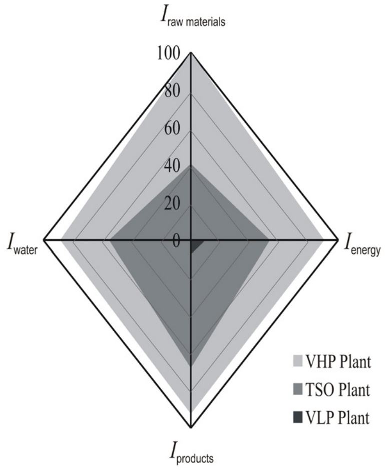

Fig. 3: The results of the performance benchmarking of the case-studied beet sugar

4. Conclusions

This model permits a combination of the various sugar production indicators, presently using different units of measurement. BAT Index, if used in several sugar plants, could become a challenge for the sugar industry. It could be used as an indicator showing improvements needed, especially when the performance is out of line with the BAT performance levels. It is important to note that this model is modular, in order to permit deletion or modification of the indicators. Its computer version in Matlab is interactive and the user is able to adjust the inputs of the model according to the data at hand. Also, there is the possibility of varying BAT Benchmarks according to the updated information.

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