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Research paper

Combining behavioural TOPSIS and six multi-criteria weighting methods to rank biomass fuel pellets for energy use in Sweden

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ABSTRACT

EU energy and climate policies continue to drive interest in biomass fuel pellets which can be produced from a wide variety of feedstock. The use of multi-criteria decision analysis (MCDA) to support feedstock selection has the potential for more transparent and better decision-making. This study applies the behavioural TOPSIS, a prominent MCDA technique, to rank pellets for energy use in Sweden produced from under-utilised forest and agricultural biomass. Seven criteria were used to assess and rank the biomass pellets. The alternatives include 88 types of pellets from 11 biomass materials. Possible attitudes of an expert towards the risk of losses (risk averse, risk neutral and risk-seeking) were combined with six sets of criteria weights obtained using six weighting methods – a total of 18 input settings (scenarios). Despite having different input settings, almost identical results were obtained in all scenarios, meaning that the rankings were stable and consistent. Across all 18 scenarios, pellets produced from a reference spruce/pine sawdust blend are ranked ahead of other pellet types. Pellets produced from Scots pine bark exhibited stable and consistent rankings across all scenarios; and thus this biomass is the second-best overall. The next best materials overall are poplar, reed canary grass and wheat straw, whereas torrefied pellets (torrefied beech, poplar and wheat straw) were ranked last in all scenarios. Combining behavioural TOPSIS and a variety of criteria-weighting methods is a meaningful way of improving decision-making with respect to producing a more valid and reliable ranking of biomass fuel pellets for energy use in Sweden.

1. Introduction

Between 2010 and 2017, the production of biomass fuel pellets grew from approximately 10 to 30 million tonnes (Thrän et al., 2017). Key drivers of this growth include: the realisation of renewable energy targets both in the EU and globally, the adoption of circular-economy approaches by the wood-processing industry, and greater utilisation of inland energy sources. Growth is expected to accelerate in the coming decades as a result of EU energy and climate policies targeting 40% emission reductions by 2030 (European Commission, 2014) and the European Green Deal's (European Commission, 2019) pursuit of carbon-neutrality in the EU by 2050.

Given existing infrastructure realities, biomass fuel pellets enable a transition from fossil coal to biomass fuel pellets in existing coal power plants (van Loo and Koppejan, 2002). This transition is via direct co-firing or complete fuel replacement, depending on pellet properties and boiler designs. Running existing coal power plants with torrefied wood pellets, for example, is an economically attractive option (Agar and Wihersaari, 2012). Notwithstanding the move to more sustainable energy sources, coal-fired plants continue to be common in Europe and especially China (Van der et al., 2017), which represents 50% of the global market for coal production (IEA).

A fundamentally important property of any fuel is its energy density (as received): i.e. the amount of energy per unit volume of fuel (GJ m^{-3}). High energy density translates to more energy being contained in less space, which has benefits for transport efficiency, including lower associated emissions from shipping, and storage (Agar et al., 2015). One of the main advantages of fossil fuels is their inherently high energy density relative to renewable fuels. Sub-bituminous coal commonly used in pulverised-fuel boilers typically has an energy density in the range of 12.8–17.8 GJ m^{-3} (ECN, 2020), whereas the achievable energy density for state-of-the-art torrefied fuel pellets has been shown to be in the range of 11.9–13.2 GJ m^{-3} (Agar et al., 2021).

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The Swedish pellet industry is an example of successful sector whose capacity has exhibited continuous growth and now feeds a large domestic and European market. Industrial-scale production commonly uses rotating ring-die mills to produce fuel pellets, with pellet standards (ENplus) playing an important role in ensuring high quality (Obernberger and Thek, 2010). These standards specify various types of pellet, depending on the end-user, but they can also limit the feedstock types used in production, sometimes due to inflexible criteria that may not necessarily be problematic in use (e.g. high-ash content fuels). Wood pellets conform to quality standards most easily but non-wood feedstocks are the targets of future increased biomass utilisation. Standards are primarily for the combustion market but take into account both large and small-scale users. Naturally, producers would prefer to minimise production costs while satisfying all quality standards.

In the case of conventional wood-pellet production, the decision-making related to which feedstock materials (biomass) to select for use is simple and straightforward. However, when there is a variety of feedstocks to choose from, evaluating them on multiple criteria explicitly leads to better decisions, but such multiple criteria decision-making inevitably involves considering trade-offs between the criteria, which is relatively complex. Multi-criteria decision-analysis (MCDA), a sub-discipline of operations research, is available to support such decision-making (Belton and Stewart, 2002; Mendoza and Martins, 2006). MCDA is concerned with formally structuring and solving decision problems, typically involving the explicit weighting of criteria and the trade-offs between them to represent the preferences of the decision-makers (DMs) (and, potentially, other stakeholders). The objective of MCDA is to support DMs to make valid and reliable decisions in a consistent and transparent fashion.

MCDA is used in many decision making problems related to energy from biomass (Sultana and Kumar, 2012), energy storage technology (Murrant and Radcliffe, 2018), biomass conversion (Kheybari et al., 2019), micro hydropower potential (Eshra et al., 2021), renewable energy investments (Karatop et al., 2021), power generation (Pavlović et al., 2021; Asakereh et al., 2022; Manirambona et al., 2022), microgrid energy management (Raghav et al., 2022), hydropower plants (Singh et al., 2021) and wind farms investments (Ziemba, 2022). Sultana and Kumar (2012) used a MCDA technique, the Preference Ranking Organization Method for Enrichment and Evaluation (PROMETHEE), to rank five fuel-pellet types produced from wood, straw, switch grass, alfalfa and poultry litter. Three modelling scenarios were evaluated, with conventional wood pellets found to be the best overall. Kheybari et al. (2019) used MCDA to evaluate technologies converting biomass to biofuels. They used an analytical hierarchy process (AHP) - one of MCDA methods — to obtain weights of criteria used for evaluation of technologies. Pavlović et al. (2021) used MCDA for assessing the potential of renewable energy sources for electricity generation in Serbia with respect to the economic, technical, environmental, and socio-political criteria. Similarly, for that purpose they used only one MCDA method named the fuzzy analytical hierarchy process (FAHP). Eshra et al. (2021) assessed in a multi-criteria context the potential of mini and micro hydropower for Egypt's main grid areas, by using a single MCDA method, named Simple additive weighting (SAW). Karatop et al. (2021) used two MCDA methods, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and AHP to determine how the optimum investment decisions could be taken in the renewable energy sector in Turkey. They analysed renewable energy alternatives which included hydropower, solar energy, wind energy, geothermal energy and biomass energy. Manirambona et al. (2022) applied a combination of AHP and TOPSIS to evaluate Kenyan power technology options using the four sustainable dimensions: economic, social, environmental and technical. The results showed that solar photovoltaic (PV) and wind are the most promising technologies in Kenya. Asakereh et al. (2022) used fuzzy AHP for ranking renewable power generation technologies (i.e., PV, concentratedsolarpower, anaerobicdigestion, direct combustion and wind energy) in the Khuzestan province of Iran. Their results showed that, PV, followed by concentrated solar power are the top priorities for renewable electricity generation. Thus, it can be stated that the use of only one or two MCDA methods in literature around renewables is a common approach.

This study applies the behavioural TOPSIS, a prominent MCDA technique, to rank (from 'best' to 'worse') 88 types of fuel pellets produced from 11 biomass materials from under-utilised forest and agricultural biomass. Seven criteria, both quantitative and qualitative in nature, were selected and used for evaluating, and, ultimately, ranking biomass pellets. These criteria (production cost, energy density, durability, ash content, sulphur content, chlorine content and feedstock availability) were selected based on general requirements and assumptions from the industrial heat and power sector.

Very important input for behavioural TOPSIS (as for other MCDA methods too) are the weights of criteria, representing their relative importance. Therefore, careful attention should be paid to how the weights are determined. As there is currently no consensus in the MCDA literature as to which criteria-weighting method is the best (Lienert et al., 2016), six widely used weighting methods were applied and combined with behavioural TOPSIS and the results compared. Five of the criteria-weighting methods are based on expert knowledge and the subjective preferences of the DM and one method is a quantitative (statistical) method.

In addition, this study incorporates DM' behavioural tendencies into the MCDA by using the behavioural TOPSIS method, which, in short, applies the important finding from behavioural economics that DMs typically feel differently about gains vis-à-vis losses (Kahneman and Tversky, 1979, 1984; Thaler, 1980). The novelty of the presented approach is as follows:

- The present study uses production data from a large industrially-relevant investigation directed at large-scale heat and power use of fuel pellets. Pilot-scale pellet production and quality characterisation of 88 types of pellets produced from 11 biomass materials was performed at the Biomass Technology Centre of the Swedish University of Agricultural Sciences in Umeå, Sweden. This highly representative data will provide valid and reliable inputs for behavioural TOPSIS.
- The use of five criteria-weighting methods based on expert knowledge and subjective preferences of the DM will minimise bias related to the selection of criteria-weighting method, something that cannot be said for previous studies that tend to use only one or two methods in combination. Using a quantitative (statistical) method will minimise bias related to subjectivity of experts or decision makers. Thus, an important contribution of the study is an examination of the sensitivity of the rankings to the method used to determine the weights on the criteria.
- This is first application of behavioural TOPSIS – as an extension of the original TOPSIS – for rankings biomass fuel pellets. Behavioural TOPSIS uses a loss aversion ratio to reflect DM attitudes towards the risk of losses when ranking biomass pellets. Additionally, we used all three loss aversion ratios (risk averse, risk neutral and risk-seeking) in order to have more robust and reliable results.

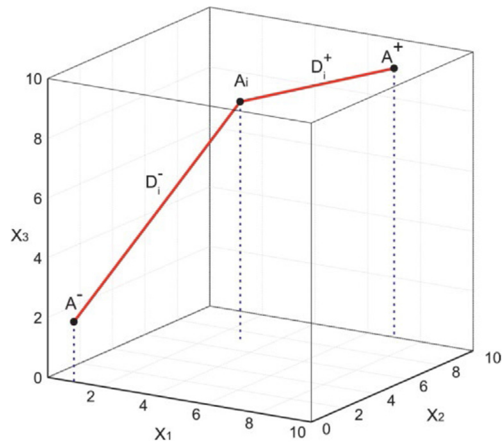


Fig. 1. Alternative A_i and its distance (D^+) from ideal alternative A^+ and distance (D^-) from anti-ideal alternative A^- (Yoon and Kim, 2017)

- Finally, the objective of this approach is to improve decision-making by combining six sets of criteria weights (obtained using six criteria-weighting methods) with three loss aversion ratios (risk averse, risk neutral and risk-seeking) and to provide 18 input settings (scenarios) for performing behavioural TOPSIS. This approach enables the rankings of biomass pellets to be compared across 18 scenarios, with the opportunity to produce a more valid and reliable ranking of biomass fuel pellets for energy use in Sweden and to identify the top-ranked pellets overall.

2. Material and methods

2.1. Methodology for biomass pellets ranking

A wide range of MCDA methods is available (Belton and Stewart, 2002). The present study uses the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), which was introduced by Hwang and Yoon (1981) and went on to become a classic and highly cited method (Yoon and Kim, 2017). The basic idea of TOPSIS is intuitive and straightforward.

TOPSIS creates two artificial extreme alternatives to be utilised as reference points — like the polar star in the heavens and the nadir point in hell (Yoon and Kim, 2017). The ideal alternative, A^+, consists of the best values on the criteria across the alternatives, whereas the anti-ideal alternative, A^-, consists of the worst criteria values. In other words, A^+ maximises the benefit criteria and minimises the cost criteria, whereas A^- maximises the cost criteria and minimises the benefit criteria (Behzadian et al., 2012). TOPSIS attempts to choose alternatives that simultaneously have the shortest Euclidean distance from the ideal alternative (D^+) and the farthest Euclidean distance from the anti-ideal alternative (D^-) (Behzadian et al., 2012). Fig. 1 shows how an alternative (A_i) with three benefit (maximisation) criteria is transformed into two distances from the ideal and anti-ideal points (Chang et al., 2010).

A common misapprehension is that TOPSIS always selects an alternative that is closest to the ideal alternative and farthest from the anti-ideal alternative simultaneously (Yoon and Kim, 2017); instead, TOPSIS calculates a value function defined as

$$C_i^+ = D_i^- / \left(D_i^+ + D_i^-\right) \tag{1}$$

and then ranks alternatives according to their C^+ values.

According to Olson (2004) and Shih et al. (2007), TOPSIS has these five advantages: (i) it is based on a sound logic representing the rationale of human choice; (ii) a scalar value is generated accounting for both the ideal and anti-ideal alternatives simultaneously; (iii) TOPSIS's simple computations are easily programmable using a spreadsheet; (iv) the alternatives' performance measures on the criteria can be visualised on a polyhedron, at least for any two dimensions; and (v) the only inputs needed from the DM are weights on the criteria, representing their relative importance.

These criteria weights are a very important input for TOPSIS (as for other MCDA methods too) because of their fundamental role in the final ranking of alternatives produced. Therefore, careful attention should be paid to how the weights are determined.

Though statistical methods can be used to determine the weights, the usual approach is to elicit and quantify DMs' preferences based on their expert knowledge and subjective judgement. A variety of methods are available for doing so, all potentially capable of producing different weights (Belton and Stewart, 2002). As already mentioned, there is currently no consensus as to which method is the best (Lienert et al., 2016), and so six widely used weighting methods are applied and their results compared.

This study utilises an augmented version of the TOPSIS: the *behavioural* TOPSIS (Yoon and Kim, 2017). This technique incorporates the idea from behavioural economics that DMs typically feel differently about gains vis-à-vis losses (Kahneman and Tversky, 1979, 1984; Thaler, 1980). Thus, as well as a DM's preferences being represented by criteria weights (as discussed above), their attitudes towards the risk of losses are represented by a loss aversion ratio to reflect their inclination in this respect when ranking biomass pellets. The approach herein is to combine six sets of criteria weights (obtained using six criteria-weighting methods) with three loss aversion ratios (risk averse, risk neutral and risk-seeking) to provide 18 input settings (scenarios) for performing behavioural TOPSIS. This approach enables the rankings of biomass pellets to be compared across 18 scenarios, with the opportunity of identifying the top-ranked pellets overall.

2.1.1. Behavioural TOPSIS

Tzeng and Huang (2011) explain that behavioural TOPSIS, as an extension to (original) TOPSIS, comes from reference-dependent theory (Kahneman and Tversky, 1979) which is a central principle in prospecttheory and behaviouraleconomics in general. Reference-dependent theory posits that consumers evaluate alternatives in terms of gains and losses relative to a subjective reference point (Kahneman and Tversky, 1979, 1984; Kahneman et al., 1991).

According to Yoon and Kim (2017), the magnitude of D_i^- in the TOPSIS can be interpreted as the *gain* that a DM accrues from taking A_i instead of anti-ideal solution A^-; similarly, the magnitude of D_i^+ can be interpreted as the *loss* (Raiffa and Games, 1968) or *opportunity cost* incurred from taking A_i instead of ideal solution A^+. Losing something hurts more than gaining something of the same magnitude. For simplicity, as we explain below, we assume that this ratio is two, so that losing something makes a person (approximately) twice as unhappy as gaining the same thing makes them happy. This means that a DM is only willing to incur one unit of loss in return for two units of gain (Yoon and Kim, 2017). Thaler (1980) called this trade-off the *endowment effect*, and Kahneman and Tversky (1984) called it as *loss aversion*.

In behavioural TOPSIS, the loss aversion ratio is defined as

$$\theta = \frac{\Delta D^-}{\Delta D^+} \tag{2}$$

where ΔD^- is change in gain, ΔD^+ is change in loss and the DM's choice behaviour is classified as being loss averse when $\theta > 1$, neutral when $\theta = 1$ and loss prone (or risk-seeking) when $\theta < 1$.

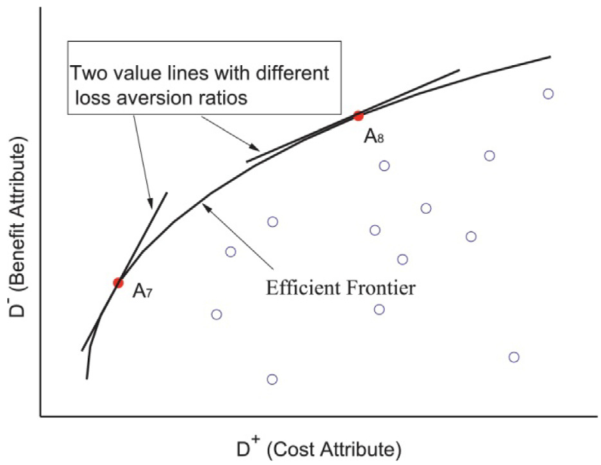


Fig. 2. Two choices with different loss aversion ratios, where first choice (A7) is highly loss averse and second choice (A8) is less loss averse (Yoon and Kim, 2017).

Instead of using the value function from the original method (Eq. (1)), behavioural TOPSIS implements the loss aversion ratio θ into a new value function:

$$V_i = D_i^- - \theta D_i^+ \tag{3}$$

Fig. 2 illustrates how different loss aversion ratios (values of θ) will affect which alternative will be selected as first ranked ('best') off the efficient frontier. A DM who is highly loss averse ($\theta > 1$, represented by the steep value line) will choose A_7, whereas another DM who is less loss averse (represented by the flatter line) will choose A_8.

In this paper we used $\theta = 2$ because behavioural economists have estimated, based on field experiments, that the loss aversion ratio is in the range of 1.5–2.5 (Novemsky and Kahneman, 2005). In addition, we used $\theta = 0.1$ for a risk-seeking scenario and $\theta = 1$ for risk neutrality. It is worthwhile noting that the original TOPSIS (i.e. without loss aversion) and behavioural TOPSIS with $\theta = 1$ both produce identical rankings of alternatives (Yoon and Kim, 2017).

The complete behavioural TOPSIS algorithm (Yoon and Kim, 2017) is presented in Steps 1–7, as follows.

Step 1: *Define an MCDA problem.*

For the number of alternatives (biomass pellets) $= n$ and number of decision criteria $= m$, the decision matrix $A = (a_{ij})$ has this form:

$$A = \begin{array}{c} \\ \\ A_1 \\ A_2 \\ \cdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_m \\ w_1 & w_2 & \cdots & w_m \end{array} \\ \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \dots & \tilde{a}_{2n} \\ \dots & \dots & \dots & \dots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & \tilde{a}_{nn} \end{bmatrix} \end{array} \tag{4}$$

where $a_{11} - a_{nm}$ are criteria values of alternatives (or scores), and $w_1 - w_m$ are weights on the criteria, whose sum is 1.

Step 2: *Construct the normalised decision matrix $R = (r_{ij})$.*

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{n} a_{ij}^2}}, i = 1, \dots, n; j = 1, \dots, m \tag{5}$$

Step 3: *Construct weighted-normalised decision matrix.*

$$v_{ij} = w_j r_{ij}, i = 1, \dots, n; j = 1, \dots, m \tag{6}$$

where w_j is the weight of the criterion j.

Step 4: *Determine the ideal alternative (A^+) and the anti-ideal alternative (A^-).*

$$\begin{aligned} A^+ &= \{v_1^+, v_2^+, \dots, v_m^+\} \\ &= \left\{ \left(\max_i v_{ij} | j \in J_1 \right), \left(\min_i v_{ij} | j \in J_2 \right) | i = 1, \dots, n \right\} \end{aligned} \tag{7}$$

$$\begin{aligned} A^- &= \{v_1^-, v_2^-, \dots, v_m^-\} \\ &= \left\{ \left(\min_i v_{ij} | j \in J_1 \right), \left(\max_i v_{ij} | j \in J_2 \right) | i = 1, \dots, n \right\} \end{aligned} \tag{8}$$

where J_1 is the set of maximisation criteria and J_2 is the set of minimisation criteria. Maximisation criteria are more preferred by DMs when they have larger criteria values, and minimisation criteria are less preferred when they have larger criteria values.

Step 5: *Calculate Euclideandistances to ideal alternative (D^+) and anti-ideal alternative (D^-).*

$$D_i^+ = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^+\right)^2}, i = 1, \dots, n \tag{9}$$

$$D_i^- = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^-\right)^2}, i = 1, \dots, n \tag{10}$$

Step 6: *Compute values for each alternative.*

(a) For original TOPSIS

$$C_i^+ = \frac{D_i^-}{D_i^+ + D_i^-}, i = 1, \dots, n \tag{11}$$

(b) For behavioural TOPSIS

$$V_i = D_i^- - \theta D_i^+, i = 1, \dots, n \tag{12}$$

Where θ is a loss aversion ratio chosen by the DM.

Step 7: *Rank alternatives according to C^+ or V.*

2.1.2. Methods for determining weights on the criteria

Six widely used methods for determining weights on the criteria are applied: five based on DMs' expert knowledge and subjective preferences (hereinafter referred to as 'preference-based weighting methods', PWMs) and one based on quantitative (statistical) methods.

The five PWMs are: direct point allocation (DIRECT), Simple Multi-Attribute Rating Technique (SMART) (Edwards, 1977; von Winterfeldt and Edwards, 1986), SWING (von Winterfeldt and Edwards, 1986), Analytic Hierarchy Process (AHP) (Saaty, 1980) and the Potentially All Pairwise RanKings of all possible Alternatives (PAPRIKA) method (Hansen and Ombler, 2008).

Possible quantitative methods include the Entropy method (Shannon and Weaver, 1947; Srdjevic et al., 2004) and the Criteria Importance Through Inter-criteria Correlation (CRITIC) method (Diakoulaki et al., 1995). Quantitative methods are less commonly used than PWMs because they are blind to problem reality: i.e. the weights are allocated based on the observed level of variation within each criterion rather than on problem-related values (Blagojevic et al., 2019). Nonetheless, for comparison purposes, the Entropy Method (EM) was used.

These six methods – DIRECT, SMART, SWING, AHP, PAPRIKA and Entropy – are now explained in turn.

The DIRECT method involves the DM allocating a total number of points, most commonly 100, across the criteria. The allocation of the points is intended to represent the relative importance, or weight, of the criteria. Whatever the total number of points allocated, the weights on the criteria are calculated (normalised) by dividing each criterion's points by the total.

Table 1
Saaty's importance scale.

Definition	Importance
Equal importance	1
Weak dominance	3
Strong dominance	5
Demonstrated dominance	7
Absolute dominance	9
Intermediate values	(2, 4, 6, 8)

The SMART method involves the DM, first, ranking the criteria and, second, assigning 10 points to the lowest-ranked criterion, and then assigning higher point values (with no upper limit) to the other criteria in proportion to their relative importance (Pöyhönen and Hämäläinen, 2001). Like the DIRECT method, the weights on the criteria are calculated by dividing each criterion's points by the sum of the points allocated.

The SWING method explicitly incorporates the criteria ranges in the elicitation questions, which requires that the minimum and maximum levels for each criterion need to be known before the process starts. The DM is first asked to imagine the "worst" alternative which has the lowest (worst) value on each criterion. They are then asked to select the criterion that delivers the greatest improvement when it 'swings' to its best value and to allocate 100 points to that criterion. Next the DM is asked to choose a criterion change from the worst to the best value which he considers to be the second most desirable improvement and to assign less than 100 points to that criterion change. This procedure is repeated with all the remaining criteria. The weights on the criteria are calculated by normalising the allocated points across the criteria to sum to one.

Thomas Saaty (1980) wanted to simplify the mental processes required in decision-making (Tsagdis, 2008) and for that purpose developed the AHP which can be used in both individual and group decision-making. A method of pairwise comparisons (introduced by Thurstone, 1927) is a key feature underpinning the popularity of AHP (Blagojevic et al., 2020) and it could be reduced to the following rule of thumb: take two at a time if you are unable to handle more than that (Koczkodaj, 1993).

The AHP method involves the DM comparing all n criteria in pairs (i.e. $n(n-1)/2$ comparisons in total), and assigning a value a_{ij} from the nine-point scale in Table 1 representing the relative importance of criterion i over criterion j.

These values are used to define a matrix A in which $a_{ii} = 1$ for all i and $a_{ij} = 1/a_{ji}$ for all i and j. The weights of the criteria are then calculated; in this study we used the logarithmic least squares prioritisation method (LLS) (Crawford and Williams, 1985), where the weights of criteria are the normalised geometric means of the rows of matrix A:

$$w_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{i=1}^{n}\left(\sqrt[n]{\prod_{j=1}^{n} a_{ij}}\right)}. \tag{13}$$

According to Schoemaker and Waid (1982), Belton (1986), Pöyhönen and Hämäläinen (2001) and Blagojević et al. (2023) the main difference between AHP and previously described DIRECT, SMART and SWING methods is that AHP produces a larger range of weights than the other weighting methods.

The PAPRIKA method involves the DM answering a series of simple pairwise-ranking questions based on choosing between two hypothetical alternatives – in the present context, biomass pellets – defined on just two criteria at a time and involving a trade-off (the other criteria are assumed the same). Each time the DM answers a question, PAPRIKA *adapts* by applying the logical property of transitivity to decide on the next question asked; e.g. if the DM ranks alternative A over B and then B over C, then by transitivity A must be ranked over C, and so a question about this third pair is not asked. Thus, PAPRIKA is recognised as a type of adaptive conjoint analysis (Green and Srinivasan, 1978). In the process of answering a relatively small number of questions, the DM ends up having pairwise ranked all hypothetical alternatives defined on two criteria at a time, either explicitly or implicitly (by transitivity). From the pairwise rankings, the weights on the criteria are calculated using linear-programming methods; technical details are in Hansen and Ombler (2008)).

The Entropy method is based on Shannon's entropy concept (Shannon and Weaver, 1947), which can be summarised as a measure of informational uncertainty. This method considers decision matrix $A = (a_{ij})$ – where the number of alternatives (biomass pellets) is n and the criteria is m (Eq. (1)) – as a specific source of information emitted through the criteria to the DM. Entropy involves measuring indeterminacy in the information transmitted by the matrix and directly generating weights on the criteria, based on the mutual contrast of individual values of alternatives for every criterion and then for all criteria simultaneously (Deng et al., 2000; Srdjevic et al., 2004; Vranešević et al., 2017). The weights are determined as follows.

First, by additive normalisation of each column in matrix A, a new matrix $R = (r_{ij})$ is obtained containing relative values of alternatives across criteria.

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{14}$$

The information contained in matrix R can be considered as the 'emission power' for each criterion and used to compute an entropy value e_j:

$$e_j = -k \sum_{i=1}^{n} r_{ij} \ln r_{ij}, \quad j = 1, 2, \ldots, m \tag{15}$$

Introducing the constant $k = 1/\ln n$ ensures that all values of e_j are within an interval [0, 1]. Then, the degree of divergence d_j of the average intrinsic information contained in each criterion is calculated as $d_j = 1 - e_j$ ($j = 1, 2, \ldots, m$). Finally, relative weights for all criteria are obtained by simple additive normalisation:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{16}$$

The larger the divergence of the initial values a_{ij} of alternatives A_i for given criterion C_j, the larger is its d_j, which indicates that the importance of the criterion C_j for the given decision-making problem is larger. Consequently, if all alternatives have similar values for a given criterion, this criterion is less important for the decision-making problem. If all values of the alternatives for a given criterion are the same, that criterion can be eliminated because it does not provide any new information to the DM (Srdjevic et al., 2004; Vranešević et al., 2017).

The entropy method is called 'unbiased' or 'objective' because the weights on the criteria are computed directly from the decision matrix, which means independently from the DM and their expert knowledge and subjective preferences. However, this property does not necessarily mean that the weights are more valid or reliable than weights obtained from the five PWMs.

2.2. Characteristics of the biomass pellets

2.2.1. Raw materials

The 11 types of biomass feedstocks used for pelleting are: a reference Norway spruce/Scots pine sawdust blend (55%–60% *Picea abies* and 40%–45% *Pinus sylvestris*) (REF), beech stem wood chips (*Fagus ssp.*) (BCH), whole stem willow chips (*Salix ssp.*)

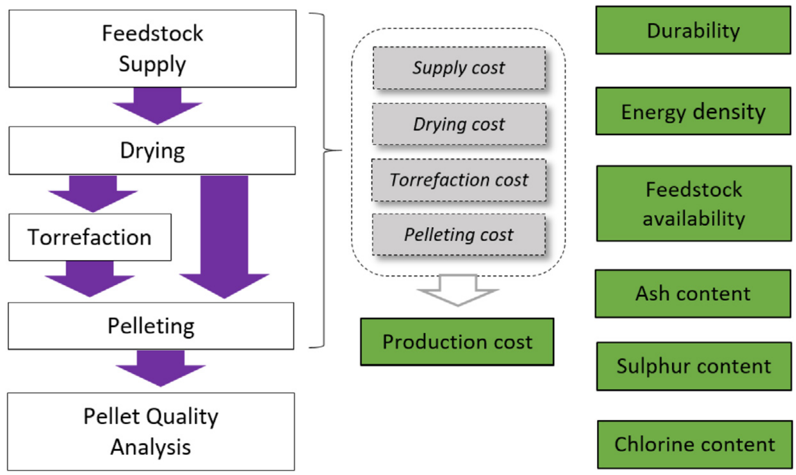


Fig. 3. The flow chart representing the pellet production process (left side) with the contributions to production cost criteria (centre) and the other six criteria used in the study (right side). All criteria are coloured green. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Average production costs of biomass fuel pellets based on pilot-scale experiences.

Feedstock	Supply €t^{-1}	Drying[a] €t^{-1}	Pelleting[a] €t^{-1}	Torrefaction €t^{-1}	Total cost[a] €t^{-1}
Reference	31.30	2.17	3.29	0.00	36.76
Beech	45.00	15.55	3.84	0.00	64.39
Salix	42.00	20.32	3.75	0.00	66.07
Poplar	40.00	11.99	3.53	0.00	55.52
Reed canary grass	48.00	1.06	2.96	0.00	52.02
Wheat straw	51.46	1.36	2.39	0.00	55.21
Forest residues	35.05	26.25	2.35	0.00	63.65
Scots pine bark	25.00	20.12	2.64	0.00	47.76
Torrefied beech	59.00	15.55	4.66	10.00	89.21
Torrefied poplar A	52.00	11.99	4.83	10.00	78.82
Torrefied poplar B	54.00	11.99	3.23	10.00	79.21
Torrefied wheat straw	66.90	1.36	4.91	10.00	83.16

[a]These costs are based on averages for each feedstock type.

(SLX), poplar stem wood chips (*Poplar ssp.*) (POP), reed canary grass (*Phalaris arundinacea*) (RCG), wheat straw (*Triticum ssp.*) (WST), forest residues (FRS), and Scots pine bark (PBK). Three varieties of torrefied materials are also used for pelleting: beech torrefied (BTF), poplar torrefied (PTF) and wheat straw torrefied (WTF).

2.2.2. *Production and cost data*

As represented in Fig. 3, pilot-scale pellet production and quality characterisation was performed at the Biomass Technology Centre of the Swedish University of Agricultural Sciences in Umeå, Sweden (see Table 2).

Feedstock cost

The reference supply cost was 31.30 €t^{-1} (Thek and Obernberger, 2004). Wheat straw and forest residue costs were taken from the recent H2020 Mobile and Flexible Industrial Processing of Biomass Project deliverables (Report on raw material availability, costs and demand) and other costs were based on relative estimates. The large surplus of pine bark in existing industries in Sweden was taken into account when estimating its supply cost. For torrefied pellets, a 30% greater supply cost was modelled, which represents the typical mass loss due to thermal degradation in existing torrefaction processes (Agar et al., 2015).

Drying cost

Drying cost were calculated using a fixed drying energy price of 0.06 €kWh^{-1} and a heat demand of 1000 kWh per tonne of evaporated water, which is within the modelled range of commercial driers (865 to 1100 kWh t^{-1}) used in wood-pellet production (Thek and Obernberger, 2004). The required drying energy (amount of water evaporated) was calculated using the difference between the determined as-received moisture content of the feedstock and the moisture content used in pelleting.

Torrefaction cost

The cost of torrefaction was modelled as a fixed extra cost of 10 €t^{-1} on top of the average drying cost. This is justifiable based on the production cost difference (7.45 €t^{-1}) between wood pellets and torrefied pellets in an established pilot-scale torrefaction process (Agar, 2017).

Pelleting cost

Pelleting costs are a function of feedstock type, the frictional forces they induce and the pelleting energy used in extruding the pellets from the die. Pelleting energy requirements with all feedstocks and 88 pellet samples was in the range of 31.3-102 kWh t^{-1}. Pelleting cost was calculated using a fixed energy (electricity) price of 0.06 €kWh^{-1}.

2.2.3. *Pellet quality characterisation*

All pellet batches produced were tested according to ENplus quality standards (Table 3). European standard (EN) methods for solid biofuels were used to characterise pellet bulk density (EN 15103), mechanical durability (EN 15210) and moisture content (EN 14774) 24 h after production.

The property values presented are averages of three replicated measurements. The as-received heating value of pellets LHV_{ar} (MJ kg^{-1}) was calculated using Eq. (17), from the European standard for determination of calorific value (EN 14918), in which M_{ar} (%)

Table 3
ENplus pellet quality requirements (ENplus).

Property	Unit	ENplus A1	ENplus A2	ENplus B
Diameter	mm	6-8		
Length	mm	$3.15 < L \leq 40$		
Moisture Content	% a.r	≤10		
Ash Content	% a.r	≤0.7	≤1.2	≤2.0
Mechanical Durability	% a.r	≥98.0	≥97.5	
Fines (< 3.15 mm)	% a.r	≤1.0		
Net calorific value	MJ kg^{-1} a.r	≥16.5		
Bulk density	kg m^{-3}	≥600		
Additives	% a.r	≤2.0		
Nitrogen	% d.b	≤0.3	≤ 0.5	≤1.0
Sulphur	% d.b	≤0.04	≤0.05	
Chlorine	% d.b	≤ 0.02		≤ 0.03
Ash Deformation Temperature	°C	≥1200	≥1100	

a.r: as received, d.b: dry basis.

Table 4
Criteria used for ranking biomass pellets in Sweden.

Criteria	Unit	Range	Type of criteria
Production cost (PC)	(€t^{-1})	34.84–89.88	Minimisation
Energy density (ED	(GJ m^{-3})	7.05–13.29	Maximisation
Durability (DU)	(%)	77.32–98.75	Maximisation
Ash content (AC)	(%)	0.50–10.00	Minimisation
Sulphur content (SC)	(%)	0.00–0.13	Minimisation
Chlorine content (CC)	(%)	0.00–0.46	Minimisation
Feedstock availability (FA)	Descriptive or qualitative	low (l), low-med (lm), med (m), med-high (mh), high (h)	Maximisation

is the as-received moisture content and LHV_{dm} (MJ kg^{-1}) is the lower heating value (dry mass). The pellet energy density (as received) σ_{ar} (MJ m^{-3}) was calculated using Eq. (18) using the bulk density of pellet (as received) ρ_{ar} (kg m^{-3}).

$$LHV_{ar} = LHV_{dm} \times (1 - 0.01M_{ar}) - 24.43M_{ar} \quad (17)$$

$$\sigma_{ar} = LHV_{ar} \times \rho_{ar} \quad (18)$$

2.2.4. Emissions from end use

Flu gas emissions (e.g. SOx and NOx) from small-scale combustion of biomass fuels can have significant environmental impacts. Herein, however, it is implicitly assumed that produced pellets will be combusted at large-scale heat and power plants, including co-firing of pellets with fossil coal. As the amounts of biomass are technically limited in co-firing applications to approximately 5%–10% (van Loo and Koppejan, 2002) and due to the more significant emissions from coal, the emission contributions from the pellets, including any variation in boiler efficiency with their use, are assumed to negligible and within the routine operation of the power plants.

2.3. Decision-making problem (decision-maker, criteria and alternatives)

Decision-making was carried out by a recognised expert in biomass fuel pellet production. Five PWMs (DIRECT, SMART, SWING, AHP and PAPRIKA) were used in defining the weights of criteria.

Seven criteria were selected and used for analysis and rankings of biomass pellets (Table 4): production cost (PC), energy density (ED), durability (DU), ash content (AC), sulphur content (SC), chlorine content (CC) and feedstock availability (FA). The first six criteria are quantitative in nature and the seventh is descriptive (or qualitative) because obtaining quantitative information for it was impossible. Also, as detailed in Table 4, four of the criteria are minimisation criteria (where minimal values are ideal and maximal values are anti-ideal) and three are maximisation criteria (maximal values are ideal and minimal values are anti-ideal).

Eleven biomass materials are used for pellets, with a total of 88 types of biomass pellet: REF – 8 types; BCH – 8 types; SLX – 8 types; POP – 8 types; RCG – 8 types; WST – 8 types; FRS – 8 types; PBK – 8 types; BTF – 7 types; PTF – 13 types; and WTF – 4 types. Each type represents a biomass pellet (or 'alternative') for MCDA analysis. These 88 biomass pellets are listed in Table A.1. (An alternative approach would be to use average values for each of the 11 biomass materials but then the MCDA analysis would be less accurate and valuable information would be lost.)

3. Results and discussion

The weights on the criteria from applying the six weighting methods are reported in Table 5. It can be seen that the most important criterion to the expert is production costs (PC), with the five PWMs (DIRECT, SMART, SWING, AHP and PAPRIKA) generating weights for this criterion in the range of 0.300 (PAPRIKA) to 0.408 (SWING). The second most important criterion is durability (DU), with weights in the range of 0.200 (DIRECT and PAPRIKA) to 0.280 (AHP). Energy density (ED) was ranked third, with a mean weight of 0.117. Four of the five PWMs (DIRECT, SMART, SWING and AHP) ranked the sulphur content (SC) criterion as least important.

These results with respect to PC and ED in particular have face validity, as PC and ED are always important for the heat and power sector given that minimising PC and maximising ED contribute directly to profitability. Utilising low-cost fuels is also the prime objective of power plants where high- and low-quality fuels are often blended in the fuel yard so that boiler combustion efficiency remains constant; a high ED therefore enables greater operational utility and generally outweighs consideration of emissions (e.g. SOx and NOx) which are routinely managed at large-scale facilities.

Overall, the PWM weights revealed that the expert had stable and consistent preferences across the different weighting methods used. With respect to future multi-criteria analyses, this finding suggest that these methods produce reliable weights.

In contrast to the PWMs, the Entropy method generated very different results. Approximately equal weights are given to four of

Table 5
Weights on the criteria and their ranks (in parenthesis) from using the six weighting methods.

	PC (€/t) min	ED (GJ/m^3) max	DU (%) max	AC (%) min	SC (%) min	CC (%) min	FA descriptive max
DIRECT	0.367 (1)	0.133 (3-4)	0.200 (2)	0.067 (5-6)	0.033 (7)	0.067 (5-6)	0.133 (3-4)
SMART	0.357 (1)	0.107 (3-5)	0.214 (2)	0.107 (3-5)	0.036 (7)	0.071 (6)	0.107 (3-5)
SWING	0.408 (1)	0.082 (5)	0.204 (2)	0.122 (3-4)	0.020 (7)	0.041 (6)	0.122 (3-4)
AHP	0.384 (1)	0.061 (5)	0.280 (2)	0.153 (3)	0.027 (7)	0.063 (4)	0.032 (6)
PAPRIKA	0.300 (1)	0.200 (2-3)	0.200 (2-3)	0.042 (7)	0.142 (4)	0.050 (6)	0.067 (5)
Average of PWM	0.363 (1)	0.117 (3)	0.220 (2)	0.098 (4)	0.052 (7)	0.058 (6)	0.092 (5)
Entropy	0.150 (3-4)	0.151 (1-2)	0.151 (1-2)	0.143 (5)	0.133 (6)	0.123 (7)	0.150 (3-4)

* PC-production cost, ED-energy density, DU-durability, AC-ash content, SC-sulphur content, CC-chlorine content, FA-feedstock availability.

the criteria: ED (0.151), DU (0.151), PC (0.150) and FA (0.150). Last ranked was CC with a weight of 0.123. The scenario with different weights of criteria (i.e. the one excluding expert opinion) was effective because of the stability of biomass rankings it generated.

The results from ranking the biomass-pellet types using behavioural TOPSIS with three behavioural tendencies (risk averse, risk neutral and risk-seeking) combined with six criteria weighting methods – i.e. 18 input settings (scenarios), in total – are presented in Table B.1 and Fig. 4. It can be seen that in the risk-averse scenario, pellet type REF3 is ranked first four times (for weights using DIRECT, SMART, SWING and AHP), and REF2 is ranked first when weights are obtained using Entropy and PAPRIKA. In the risk-neutral scenario, the results for the first-ranked alternatives are almost identical. The only difference is that REF1 is first ranked when Entropy-derived weights are used. In the risk-seeking scenario, the dominant alternative is REF4: it is first ranked in all scenarios using the five PWMs (DIRECT, SMART, SWING, AHP and PAPRIKA). REF3 is ranked first when the Entropy weighting method is used.

In all 18 input settings, all pellets produced using the reference blend are ranked ahead of the other pellets. This means that REF1 to REF8 are ranked between 1st and 8th (Table B.1). Therefore, it can be concluded that REF (reference wood pellets) has the best properties for biomass-pellet production. This result is not surprising given the importance of production cost (REF are the lowest price pellets because they are produced from low cost by-products from the wood processing sector).

Biomass pellets produced from pine bark (PBK) are characterised by stable and consistent rankings in all 18 scenarios. Pellet types PBK1-8 are all ranked between 9th and 16th. Therefore, it can be concluded that pine bark has the second-best properties for biomass-pellet production.

POP, RCG and WST are the three next best pellets material in all 18 scenarios. Adjacent rankings of RCG and WST could be expected based on the fact that they are both non-woody plants, with similar physical properties, comparably high sulphur and chlorine contents, and the rely on the same harvesting and processing methods (and therefore have similar supply costs).

Beech pellets (BCH1-8) are higher ranked than the other non-conventional feedstocks considered. Torrefied pellets – beech torrefied (BTF1-7), poplar torrefied (PTF1-13) and wheat straw torrefied (WTF1-4) – are lowest ranked (from 65th to 88th, or last, place) in all 18 scenarios. The question for torrefied fuels has always been: Does the extra cost of torrefaction justify the benefits? In this study, it would seem not.

However, this study largely ignored combustion end-use scenarios, other than assuming they are routine and large-scale. The overwhelmingly predominant application of torrefied fuels is to offset coal in existing pulverised-fuel boilers. It is only in such boilers that torrefaction enables larger co-firing rates (up to 100% replacement) without infrastructure modifications (Agar et al., 2021). The significance of this is a huge emission reduction potential that is not considered herein simply because non-torrefied fuels cannot enable the same emission reduction potential at coal plants.

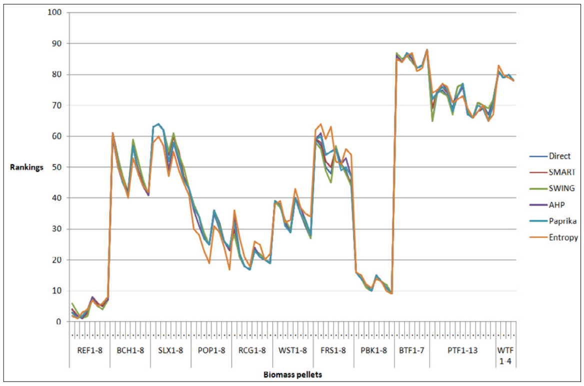
As we mentioned, MCDA is used in many decision making problems related to renewable energy. Sultana and Kumar (2012) used PROMETHEE method to rank five fuel-pellet types produced from wood, straw, switch grass, alfalfa and poultry litter. Three modelling scenarios were evaluated, with conventional wood pellets found to be the best overall. Unfortunately, this study suffered from a lack of systematic data on pellet-production methods, especially with respect to non-conventional feedstock types and so data from a wide variety of studies employing different methods and pellet characterisations had to be used. In contrast, the present study uses industrially-representative production data from a large industrially-relevant investigation directed at large-scale heat and power use of fuel pellets, which is a significant advantage. Another weakness of Sultana and Kumar (2012) is its assumptions about problematic combustion emissions and the emission data from the literature that were used but without considering the relevant boiler technologies and scales of production. A proper evaluation of pellets that enables the influence of feedstock choices to be validly compared requires consideration of their production methods based on relevant technologies (ring-die pellet mills) and production scale.

This study was design for a single decision maker to participate in the process of defining weights of criteria. There were two main reasons for this choice:

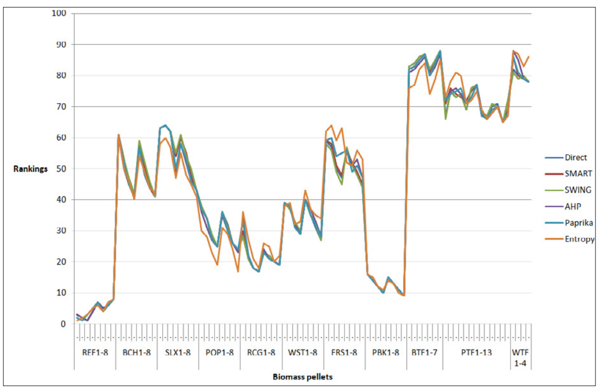
- Saaty and Özdemir (2014) examined the question of how many DMs are needed to obtain valid and consistent judgements when using the MCDA. They highlighted that if a DM is experienced and well versed in an area, efforts to add additional experts can in fact compromise the accuracy of a study if their expertise is not well balanced. It can be concluded that expert-based analyses do not need a large number of responses because they are not based on frequentist methods (Saaty and Özdemir, 2014).
- The role of the DM in this study was only to define the weights of criteria using five PWMs. In addition, MCDA was used in the scenarios with very different weights of criteria (for instance weights obtained by PWMs compared to weights obtained by the Entropy method). Despite that, almost identical rankings of biomass pellets were obtained which means that adding new DMs will most likely not produce any significant changes in the final ranking. Therefore it is concluded that one DM with proper expertise and experience is sufficient for this analysis.

4. Conclusion

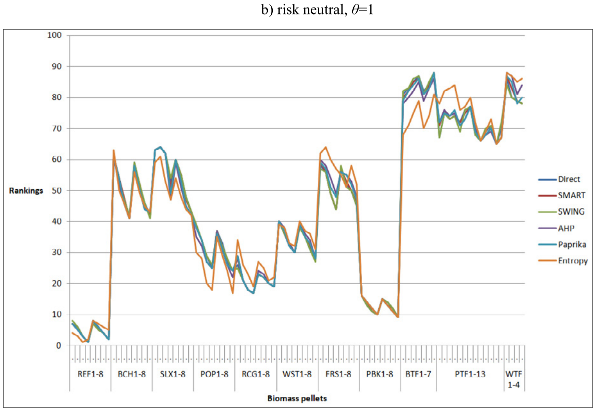
This study applies the behavioural TOPSIS combined with a variety of criteria-weighting methods, to rank pellets for energy use in Sweden produced from under-utilised forest and agricultural biomass. With the lack of consensus as to which



a) risk averse, θ=2



b) risk neutral, θ=1



c) risk seeking, θ=0.1

Fig. 4. Behavioural TOPSIS: rankings of biomass pellets.

criteria-weighting method is best, this study applied six different weighting methods in order to compared the resulting rankings of 88 biomass fuel pellets types in large-scale power generation. Five of the criteria-weighting methods are based on expert knowledge and the subjective preferences of the decision maker and one method is a quantitative (statistical) method. The different weights on the criteria and the different behavioural tendencies (risk averse, risk neutral and risk-seeking) did not significantly change the rankings of the pellets; therefore, we can conclude that our results were very stable and consistent. On the other hand, if different criteria were to be used, then different rankings could arise.

We chose the used criteria because we had reliable data for them, which strengthens confidence in our findings. However, these criteria may not be the best ones in future as alternative data in the field may be found to be more relevant. For example, environmental impact criteria determined through life-cycle assessment and policy towards resource use (especially from forests) will surely grow in importance. These are likely, and positive, developments given the need for renewable fuels to satisfied future energy and climate goals.

Nomenclature

AC	ash content (%)
BCH	beech
BTF	beech torrefied
CC	chlorine content (%)
DU	durability (%)
ED	energy density (GJ m^{-3})
FA	feedstock availability
FRS	forest residues
PBK	Scots pine bark
PC	production costs (€t^{-1})
POP	poplar
PTF	poplar torrefied
PWM	preference-based weighting method
RCG	reed canary grass
REF	reference
SLX	salix
SC	sulphur content (%)
WST	wheat straw
WTF	wheat straw torrefied
LHV_{ar}	heating value of pellets, as received (MJ kg^{-1})
LHV_{dm}	lower heating value, dry mass (MJ kg^{-1})
M_{ar}	moisture content, as received (%)
σ_{ar}	energy density, as received (MJ m^{-3})
ρ_{ar}	bulk density, as received (kg m^{-3})

CRediT authorship contribution statement

David A. Agar: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Paul Hansen:** Methodology, Writing – review & editing. **Magnus Rudolfsson:** Investigation, Writing – review & editing. **Boško Blagojević:** Conceptualization, Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of competing interest

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.

Data availability

Data will be made available on request

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Appendix A

See Table A.1.

Appendix B

See Table B.1.

Table A.1
The 88 types of biomass pellets and their values on the six criteria.

Alternatives			Criteria						
Biomass materials	Number of types	Name of pellet types	PC (€t^{-1})	ED (GJ m^{-3})	DU (%)	AC (%)	SC (%)	CC (%)	FA descriptive
Reference (55-60% *Picea abies* and 40-45% *Pinus sylvestris*)	8	REF1	38.79	11.78	96.93	0.5	0.01	0	mh
		REF2	37.71	10.96	96.93	0.5	0.01	0	mh
		REF3	36.64	10.02	96.33	0.5	0.01	0	mh
		REF4	34.97	9.03	94.13	0.5	0.01	0	mh
		REF5	38.06	10.60	93.23	0.5	0.01	0	mh
		REF6	36.94	10.06	93.93	0.5	0.01	0	mh
		REF7	36.10	9.43	93.44	0.5	0.01	0	mh
		REF8	34.84	8.62	92.07	0.5	0.01	0	mh
Beech stem wood chips (*Fagus ssp.*)	8	BCH1	65.55	9.49	87.62	0.8	0	0.02	lm
		BCH2	64.74	9.44	93.47	0.8	0	0.02	lm
		BCH3	64.27	9.13	96.51	0.8	0	0.02	lm
		BCH4	63.33	9.14	96.76	0.8	0	0.02	lm
		BCH5	65.47	9.55	91.87	0.8	0	0.02	lm
		BCH6	64.55	9.27	93.60	0.8	0	0.02	lm
		BCH7	64.06	8.90	96.20	0.8	0	0.02	lm
		BCH8	63.12	8.44	95.47	0.8	0	0.02	lm
Whole stem willow chips (*Salix ssp.*)	8	SLX1	67.85	10.94	96.13	2.3	0.03	0	m
		SLX2	68.08	10.82	95.80	2.3	0.03	0	m
		SLX3	67.91	10.73	97.20	2.3	0.03	0	m
		SLX4	65.44	10.10	98.40	2.3	0.03	0	m
		SLX5	66.13	9.23	93.73	2.3	0.03	0	m
		SLX6	65.20	9.21	95.67	2.3	0.03	0	m
		SLX7	64.42	8.91	97.33	2.3	0.03	0	m
		SLX8	63.52	8.52	97.33	2.3	0.03	0	m
Poplar stem wood chips (*Poplar ssp.*)	8	POP1	57.45	10.58	96.47	2.8	0	0	m
		POP2	56.51	10.03	97.40	2.8	0	0	m
		POP3	55.20	9.47	98.40	2.8	0	0	m
		POP4	54.73	9.15	98.73	2.8	0	0	m
		POP5	56.16	9.13	90.91	2.8	0	0	m
		POP6	55.57	9.03	94.28	2.8	0	0	m
		POP7	54.71	8.79	96.95	2.8	0	0	m
		POP8	53.83	8.19	97.52	2.8	0	0	m
Reed canary grass (*Phalaris arundinacea*)	8	RCG1	53.18	8.08	85.15	6.6	0.08	0.06	m
		RCG2	51.94	8.26	90.92	6.6	0.08	0.06	m
		RCG3	51.50	7.99	92.94	6.6	0.08	0.06	m
		RCG4	50.87	7.42	93.00	6.6	0.08	0.06	m
		RCG5	52.68	8.71	92.37	6.6	0.08	0.06	m
		RCG6	52.51	8.51	92.96	6.6	0.08	0.06	m
		RCG7	51.82	7.89	93.74	6.6	0.08	0.06	m
		RCG8	51.67	7.48	93.44	6.6	0.08	0.06	m
Wheat straw (*Triticum ssp.*)	8	WST1	56.38	8.77	86.01	9.3	0.13	0.46	h
		WST2	55.22	7.88	84.22	9.3	0.13	0.46	h
		WST3	55.38	8.32	93.55	9.3	0.13	0.46	h
		WST4	54.50	7.42	92.16	9.3	0.13	0.46	h
		WST5	55.98	8.12	83.12	9.3	0.13	0.46	h
		WST6	55.49	8.10	89.05	9.3	0.13	0.46	h
		WST7	54.92	7.49	90.95	9.3	0.13	0.46	h
		WST8	53.82	7.05	90.95	9.3	0.13	0.46	h
Forest residues	8	FRS1	64.69	9.63	84.59	2.2	0.03	0	h
		FRS2	64.05	9.05	80.85	2.2	0.03	0	h
		FRS3	63.10	8.55	83.34	2.2	0.03	0	h
		FRS4	62.10	8.05	78.21	2.2	0.03	0	h
		FRS5	65.22	10.36	91.16	2.2	0.03	0	h
		FRS6	64.19	9.76	90.47	2.2	0.03	0	h
		FRS7	63.34	9.00	85.55	2.2	0.03	0	h
		FRS8	62.48	8.54	84.63	2.2	0.03	0	h
Scots pine bark (*Pinus sylvestris*)	8	PBK1	49.33	12.45	92.13	2.8	0.03	0.08	h
		PBK2	48.33	12.05	92.47	2.8	0.03	0.08	h
		PBK3	46.96	11.54	93.20	2.8	0.03	0.08	h
		PBK4	45.98	10.94	92.73	2.8	0.03	0.08	h
		PBK5	49.50	12.73	94.23	2.8	0.03	0.08	h
		PBK6	48.68	12.48	94.59	2.8	0.03	0.08	h
		PBK7	47.20	11.85	94.36	2.8	0.03	0.08	h
		PBK8	46.05	11.18	94.24	2.8	0.03	0.08	h

(continued on next page)

Table A.1 (*continued*).

Alternatives			Criteria						
Biomass materials	Number of types	Name of pellet types	PC (€t^{-1})	ED (GJ m^{-3})	DU (%)	AC (%)	SC (%)	CC (%)	FA descriptive
Beech torrefied	7	BTF1	89.68	12.18	98.75	1	0	0	lm
		BTF2	89.33	11.40	98.32	1	0	0	lm
		BTF3	89.43	10.79	97.46	1	0	0	lm
		BTF4	88.73	10.34	95.26	1	0	0	lm
		BTF5	88.55	11.88	98.23	1	0	0	lm
		BTF6	88.85	11.56	97.23	1	0	0	lm
		BTF7	89.88	10.74	94.73	1	0	0	lm
Poplar torrefied	13	PTF1	77.70	13.29	77.61	3	0	0	m
		PTF2	78.85	13.01	80.53	3	0	0	m
		PTF3	78.61	12.58	77.32	3	0	0	m
		PTF4	78.64	12.29	78.42	3	0	0	m
		PTF5	78.64	13.24	87.53	3	0	0	m
		PTF6	79.54	12.78	87.47	3	0	0	m
		PTF7	79.78	12.63	85.80	3	0	0	m
		PTF8	78.87	12.36	90.24	3	0	0	m
		PTF9	79.01	12.12	92.70	3	0	0	m
		PTF10	79.32	11.64	92.22	3	0	0	m
		PTF11	79.11	11.05	91.00	3	0	0	m
		PTF12	79.35	12.17	95.60	3	0	0	m
		PTF13	79.62	11.36	93.53	3	0	0	m
Wheat straw torrefied	4	WTF1	83.38	12.91	85.67	10	0.13	0.23	h
		WTF2	82.47	12.31	86.60	10	0.13	0.23	h
		WTF3	84.23	11.88	94.47	10	0.13	0.23	h
		WTF4	82.57	10.88	91.20	10	0.13	0.23	h

* PC-production cost, ED-energy density, DU-durability, AC-ash content, SC-sulphur content, CC-chlorine content, FA-feedstock availability.

Table B.1
Rankings of biomass pellets for 18 input settings (scenarios).

	Behavioural TOPSIS																	
	Risk averse ($\theta = 2$)						Risk neutral ($\theta = 1$)						Risk seeking ($\theta = 0.1$)					
	D	SM	SW	A	P	E	D	SM	SW	A	P	E	D	SM	SW	A	P	E
REF1	4	4	6	3	3	2	3	3	3	3	2	**1**	7	7	8	7	7	4
REF2	2	2	3	2	**1**	**1**	2	2	2	2	**1**	2	6	5	6	5	5	3
REF3	**1**	**1**	**1**	**1**	2	3	**1**	**1**	**1**	**1**	3	3	3	3	3	3	3	**1**
REF4	3	3	2	4	4	4	4	4	4	4	5	5	**1**	**1**	**1**	**1**	**1**	2
REF5	8	8	8	8	7	7	7	7	7	7	7	6	8	8	7	8	8	8
REF6	6	6	5	5	5	5	5	5	5	5	4	4	5	6	5	6	6	7
REF7	5	5	4	6	6	6	6	6	6	6	6	7	4	4	4	4	4	6
REF8	7	7	7	7	8	8	8	8	8	8	8	8	2	2	2	2	2	5
BCH1	61	61	60	60	61	61	61	61	60	61	61	61	61	61	61	61	61	63
BCH2	53	53	53	50	51	50	53	53	53	50	52	50	54	54	53	52	54	50
BCH3	46	46	47	45	45	46	46	46	47	45	45	46	47	48	47	46	46	46
BCH4	42	42	42	42	41	40	42	42	42	41	41	40	41	41	42	41	41	41
BCH5	58	57	59	57	57	53	58	57	59	57	57	54	59	58	59	57	58	56
BCH6	52	49	52	48	48	48	52	50	52	48	48	49	51	52	52	50	50	49
BCH7	45	44	46	44	44	44	45	44	46	44	44	44	46	45	46	44	44	45
BCH8	41	41	41	41	42	42	41	41	41	42	42	42	42	42	41	43	43	43
SLX1	63	63	63	63	63	58	63	63	63	63	63	58	63	63	63	63	63	59
SLX2	64	64	64	64	64	60	64	64	64	64	64	60	64	64	64	64	64	61
SLX3	62	62	62	62	62	57	62	62	62	62	62	57	62	62	62	62	62	53
SLX4	55	54	55	49	52	47	54	54	55	49	50	47	53	51	54	47	49	47
SLX5	60	60	61	58	58	55	60	60	61	58	58	55	60	60	60	59	60	54
SLX6	54	55	54	52	53	49	55	55	54	52	53	48	55	55	55	51	53	48
SLX7	47	47	50	46	46	45	48	47	50	46	46	45	48	47	48	45	45	44
SLX8	43	43	43	43	43	41	43	43	43	43	43	41	43	43	43	42	42	42
POP1	38	37	38	36	37	30	38	37	38	36	37	30	38	38	39	35	38	30
POP2	34	34	34	31	34	28	34	34	34	31	34	28	34	34	34	32	34	28
POP3	28	27	29	27	27	23	28	27	29	27	27	23	29	27	29	27	27	20
POP4	25	25	25	25	25	19	25	25	25	25	25	19	25	25	26	25	25	18
POP5	36	36	36	35	36	31	36	36	36	35	36	31	37	37	37	37	36	35
POP6	32	31	31	30	30	29	32	31	31	30	30	29	33	31	32	31	31	29
POP7	26	26	26	26	26	24	26	26	26	26	26	24	27	26	28	26	26	24
POP8	24	24	24	23	24	17	24	24	24	23	24	17	24	24	24	22	24	17

(*continued on next page*)

Table B.1 (*continued*).

	Behavioural TOPSIS																	
	Risk averse ($\theta = 2$)						Risk neutral ($\theta = 1$)						Risk seeking ($\theta = 0.1$)					
	D	SM	SW	A	P	E	D	SM	SW	A	P	E	D	SM	SW	A	P	E
RCG1	30	30	28	34	32	36	30	30	28	34	33	36	26	28	25	29	29	34
RCG2	21	21	21	22	22	27	21	21	21	22	22	27	21	21	21	21	21	26
RCG3	18	18	18	18	18	21	18	18	18	18	18	21	18	18	18	18	18	23
RCG4	17	17	17	17	17	18	17	17	17	17	17	18	17	17	17	17	17	19
RCG5	23	23	23	24	23	26	23	23	23	24	23	26	23	23	23	24	23	27
RCG6	22	22	22	21	21	25	22	22	22	21	21	25	22	22	22	23	22	25
RCG7	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	21
RCG8	19	19	19	19	19	22	19	19	19	19	19	22	19	19	19	19	19	22
WST1	39	39	39	39	39	38	39	39	39	39	39	38	40	40	40	40	40	39
WST2	37	38	37	38	38	39	37	38	37	38	38	39	36	36	36	38	37	38
WST3	33	32	33	32	31	32	33	32	33	32	31	32	32	33	33	33	32	33
WST4	29	29	30	29	29	33	29	29	30	29	29	33	30	30	30	30	30	32
WST5	40	40	40	40	40	43	40	40	40	40	40	43	39	39	38	39	39	40
WST6	35	35	35	37	35	37	35	35	35	37	35	37	35	35	35	36	35	37
WST7	31	33	32	33	33	35	31	33	32	33	32	35	31	32	31	34	33	36
WST8	27	28	27	28	28	34	27	28	27	28	28	34	28	29	27	28	28	31
FRS1	59	59	58	59	59	62	59	59	58	59	59	62	58	59	57	60	59	62
FRS2	57	58	56	61	60	64	57	58	56	60	60	64	56	56	56	58	57	64
FRS3	50	52	49	54	54	59	50	51	49	54	54	59	49	49	49	54	51	60
FRS4	48	50	45	55	55	63	47	48	45	55	55	63	44	44	44	49	48	57
FRS5	56	56	57	56	56	52	56	56	57	56	56	52	57	57	58	56	56	55
FRS6	51	51	51	51	49	51	51	52	51	51	49	51	52	53	51	55	55	51
FRS7	49	48	48	53	50	56	49	49	48	53	51	56	50	50	50	53	52	58
FRS8	44	45	44	47	47	54	44	45	44	47	47	53	45	46	45	48	47	52
PBK1	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16
PBK2	14	14	14	14	14	15	14	14	14	14	14	15	13	14	13	14	14	14
PBK3	12	12	11	12	12	12	12	12	12	12	12	12	11	11	11	12	12	12
PBK4	10	10	10	10	10	11	10	10	10	10	10	11	10	10	10	10	10	10
PBK5	15	15	15	15	15	14	15	15	15	15	15	14	15	15	15	15	15	15
PBK6	13	13	13	13	13	13	13	13	13	13	13	13	14	13	14	13	13	13
PBK7	11	11	12	11	11	10	11	11	11	11	11	10	12	12	12	11	11	11
PBK8	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9
BTF1	86	86	87	86	85	85	83	82	83	81	82	76	81	80	82	78	79	68
BTF2	84	84	85	84	84	84	84	83	84	82	83	77	83	82	83	80	82	71
BTF3	87	87	86	87	87	86	86	85	86	84	85	82	85	85	86	82	84	75
BTF4	85	85	84	85	86	87	87	87	87	86	87	84	87	86	87	85	86	79
BTF5	82	82	82	82	82	81	81	81	82	80	80	74	82	81	81	79	81	70
BTF6	83	83	83	83	83	82	85	84	85	83	84	79	84	84	85	83	83	74
BTF7	88	88	88	88	88	88	88	88	88	87	88	85	88	88	88	86	88	81
PTF1	65	69	65	72	72	74	67	71	66	72	72	73	67	71	67	72	72	78
PTF2	74	75	75	74	74	75	75	76	75	75	74	78	75	76	75	76	75	82
PTF3	75	76	74	77	76	77	73	74	73	76	75	81	73	73	73	74	74	83
PTF4	73	74	73	75	75	76	74	73	74	74	76	80	74	74	74	75	76	84
PTF5	69	68	67	71	68	71	69	72	69	71	71	71	72	72	69	71	71	76
PTF6	76	73	76	73	73	72	76	75	76	73	73	72	76	75	76	73	73	77
PTF7	77	77	77	76	77	73	77	77	77	77	77	75	77	77	77	77	77	80
PTF8	68	67	68	67	67	69	68	67	68	69	67	69	68	69	68	70	69	72
PTF9	66	66	66	66	66	66	66	66	67	66	66	66	66	66	66	66	66	66
PTF10	71	71	71	68	70	68	70	68	71	68	69	68	69	68	70	68	68	69
PTF11	70	70	70	69	69	70	71	70	70	70	70	70	71	70	71	69	70	73
PTF12	67	65	69	65	65	65	65	65	65	65	65	65	65	65	65	65	65	65
PTF13	72	72	72	70	71	67	72	69	72	67	68	67	70	67	72	67	67	67
WTF1	81	81	81	81	81	83	82	86	81	88	86	88	86	87	84	88	87	88
WTF2	79	79	79	79	79	80	80	80	79	85	81	87	80	83	80	87	85	87
WTF3	80	80	80	80	80	79	79	79	80	79	79	83	79	79	79	81	78	85
WTF4	78	78	78	78	78	78	78	78	78	78	78	86	78	78	78	84	80	86

D-DIRECT, SM-SMART, SW-SWING, A-AHP, P-PAPRIKA, E-Entropy;
REF- reference (55-60% *Picea abies* and 40-45% *Pinus sylvestris*), BCH-beech stem wood chips (*Fagus ssp.*), SLX-whole stem willow chips (*Salix ssp.*), POP-poplar stem wood chips (*Poplar ssp.*), RCG-reed canary grass (*Phalaris arundinacea*), WST-wheat straw (*Triticum ssp.*), FRS-forest residues, PBK-Scots pine bark, BTF-beech torrefied, PTF-poplar torrefied, WTF-wheat straw torrefied.

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