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Abstract

Purpose – The purpose of this paper is thus to develop a hybrid decision-making model for optimal coal blending strategy. Coal is one of the major resources contributing to generation of electricity and anthropogenic carbon-dioxide emission. Being formed from dead plant matter, it undergoes a series of morphological changes from peat to lignite, and finally to anthracite. Because of non-uniform distribution of coal over the whole earth and continuous variation in its compositions, coals mined from different parts of the world have widely varying properties. Hence, it requires an ideal blending strategy such that the coking coal having the optimal combination of all of its properties can be used for maximum benefit to the steel making process.

Design/methodology/approach – In this paper, a multi-criteria decision-making approach is proposed while integrating preference ranking organization method for enrichment of evaluations (PROMETHEE II and V) and geometrical analysis for interactive aid (GAIA) method to aid in formulating an optimal coal blending strategy. The optimal decision is arrived at while taking into account some practical implications associated with blending of coal, such as coal price from different reserves.

Findings – Different grades of coal are ranked from the best to the worst to find out the composition of constituent coals in the final blending process. Coals from the mines of two different geographical regions are considered here so as to prove the applicability of the proposed model. Adoption of this hybrid decision-making model would subsequently improve the performance of coal after blending and help in addressing some sustainability issues, like less pollution.

Originality/value – As this model takes into account the purchase price of coals from different reserves, it is always expected to provide more realistic solutions. Thus, it would be beneficial to deploy this decision-making model to different blending optimization problems in other spheres of a manufacturing industry. This model can further accommodate some more realistic criteria, such as availability of coal in different reserves as a topic of future research work.

Keywords Decision making, Linear programming, Cost analysis

Paper type Research paper

1. Introduction

Coal, being a non-renewable resource of energy, is formed from dead flora, buried under the earth millions of years ago, because of the effects of varying temperature and pressure. Coal is elementarily composed of carbon, oxygen, hydrogen, nitrogen, moisture and other non-combustible inorganic matters. Thus, the natural constituents of coal can be broadly classified into organic matter and inorganic matter. The organic constituents are generally called as macerals, which are analogous to minerals in inorganic rocks. The amount of macerals and volatile matter in a particular coal specimen is largely influenced by the post depositional chemical environmental conditions, exposed to the acid peat (Francis, 1954). Thus, its composition, sulphur content, calorific value etc. vary from one coal reserve to another coal reserve.

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Coal blending is the process of mixing coals in a prudent way after coal has been mined to achieve quality characteristics which are desirable for the coal's intended application, e.g. steam generation in thermal power plant, coking in steel production etc. The quality characteristics that are most important in blending usually differ from one mine site to another, and also depend on how the coal seams vary in quality and their final intended use. For thermal power plant applications, the most desirable coal properties often include ash content, volatile matter, total sulphur content and gross calorific value. On the other hand, for coking coals, some other additional characteristics, like crucible swelling number, fluidity etc. are required. Blending of coal is highly practiced for combustion and gasification in thermal power plants which is quite different from blending for coke production in steel industry.

Generally, in coal blending process, any two coals cannot be just mixed. For successful blending, it requires a thorough understanding of the interaction of various inorganic components of coals in the blend process and how it affects the ash behaviour, including its emissivity and thermal conductivity. In a coal blending process, various objectives are simultaneously fulfilled, like reduced production cost, low grade coals can be mixed with better grade coal, improved calorific value, increased combustion efficiency and reduced carbon loss. A proper coal blend would also ensure reduction in submicron particulate emission (Zhou *et al.*, 2010). To have an effective coal blend, various optimization tools can be employed to determine the proportion of the constituent coals in the final blend. However, before blending of coals, various parameters, like origin of the constituent coals, their inorganic and organic compositions, their combustion and grindability properties, variation in ash contents etc. need to be studied because it has been usually observed that coals with similar burning profile are expected to behave well in full scale boilers (Sloss, 2014).

Quality of raw coal is primarily determined based on several factors and also on its various physical properties, such as ash content, sulphur content, moisture content, calorific value, maximum reflectance, dilatation, free swelling index. Some of these characteristics of raw coal are beneficial for its end use while always requiring their higher values, whereas, some of them are non-beneficial in nature preferred with their lower values. Like, lower the ash content, better is the quality of coal, as it is the non-combustible residue left after burning of coal. On the other hand, higher the calorific value of coal, better is the coal suitable for the coking purpose. When heated in absence of air, coking coal has usually the ability to soften, swell and form a coherent coke structure. This property of coking coal is known as dilatation. Hence, higher the value of dilatation, better is the coking coal. Another important property which plays a crucial role in ranking of coal is its mean maximum reflectance value. The reflectance of macerals is a measure of the metamorphism or geochemical maturity that a coal has undergone. As its measurement can also be performed on oxidized coal samples, it is therefore an excellent exploration tool for determination of ranks of the considered coals (Whitacre *et al.*, 2014).

One of the major applications of coal is in the form of coke, during steel production. The main technological challenge often faced by the engineers is to obtain a coking coal having a uniform set of properties. High variability in different properties of coal imposes a problem to have an ideal coking coal with all of its properties as desired for most efficient steel production. Various environmental constraints also restrict the application of different coal grades which would often result in high emission of potential pollutants after use. Simultaneously, the alarming depletion of good quality raw coal leads to uncertain availability of several grades of coal from different mines.

This gives rise to coal blending process, which aims at solving several challenges, such as reducing the variability of the processed coal after beneficiation, reducing raw material cost, providing the required characteristics to the end products etc. Blending can take place at several points on a coal chain (Pearson, 1980), and Figure 1 provides an idea about the typical blending points in a coal chain. Blending is usually performed by stockpile stacking, which ensures homogeneity of the final blended material. Several other blending methods are also adopted by different coal industries, such as blending in bed, blending by ground hopper and blending on moving belt. In a typical coal blending process, the possibilities of having different blending constituents are quite large and it becomes a complicated task for an engineer to determine the optimal combination of different constituents in the final coal blend. These blending decisions are often based on trial and error method, and heuristics-based solutions are also sorted.

In this paper, a hybrid multi-criteria decision-making model is proposed while integrating preference ranking organization method for enrichment of evaluations (PROMETHEE) and geometrical analysis for interactive aid (GAIA) approach to determine the optimal compositions of constituent coals in the coal blending process while considering coals coming out of the mines in India and the USA. The research question addressed in this paper is to explore the possibility of developing a decision-making model which would provide a realistic decision with respect to a practically feasible blending ratio. This topic is important because when blending of coal comes into question, several other constraints (excluding material characteristics), such as availability and price need to be addressed simultaneously to make a pragmatic decision. Coal contributes to generation of electricity (secondary source of energy) as well as acts as a major source of carbon dioxide emission. Thus, its use has both positive and negative impacts on the society. As coal is primarily used as coking coal in steel production plants, it becomes necessary to look upon the benefits and harms it causes to the society. The developed model takes into account both the beneficial and non-beneficial characteristics of coal, as well as economic constraints, while providing an optimal blending decision. In this paper, various properties of coal and their influences on the performance of the coal blend are also studied. The adopted PROMETHEE-GAIA method is a combination of mathematical and visual aids, which is quite easy to interpret while incorporating the mathematical intricacies of uncertainty and randomness.

2. Literature review

2.1 Optimization of coal blending process

Shih and Frey (1995) developed a multi-objective chance-constrained optimization model for coal blending optimization while considering variability in various coal characteristics (sulphur content, ash content and heating value). Lyu *et al.* (1995) presented a goal programming model and implemented it as an effective decision support tool for coal stockyard managers to help in the coal blending process. Initial inventory, heating value, sulphur content, volatile matter and ash content were considered as the input parameters to the developed model. Wu *et al.* (1999) developed a model-based expert control strategy using back propagation artificial neural network for controlling the coal blending process in iron and steel plants. Yin *et al.* (2000) integrated a mixed-discrete variable optimization model with artificial neural network to solve a non-linear programming problem for arriving at the optimal coal blending decision. Various coal properties, like heating value, volatile matter,

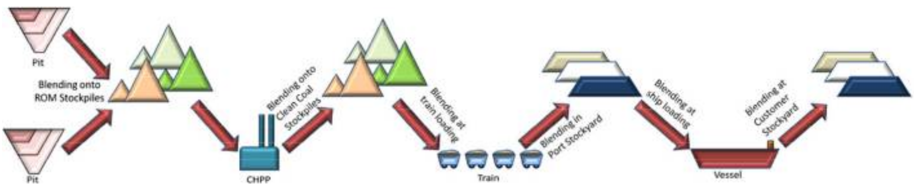

Figure 1. Typical blending points in a coal chain (Pearson, 1980)

sulphur content, moisture content, ash yield and ignition temperature were taken into account while developing the corresponding optimization problem. Erarslan *et al.* (2001) developed a linear programming (LP) model to determine the optimal coal blend composition with respect to quality and quantity (heat content and grain size). Rushdi *et al.* (2004) conducted an experimental study to investigate the effect of coal blending process on ash deposition after combustion. Exhaustive data from proximate analysis, ultimate analysis and ash analysis of the considered coals were utilized for the experimental study.

While considering fuzzy and non-linear characteristics of blended coal's slagging, Liao *et al.* (2005) presented an optimization model of power coal blending for achieving the minimum price of the blended coal. The proposed model was later solved using fuzzy neural network and genetic algorithm (GA). Liao and Ma (2006) applied a fuzzy artificial neural network-based chaos optimization algorithm for optimal coal blending, taking into consideration the slagging characteristics of blending coal as a constraint. Gupta *et al.* (2007) presented a coal blending model while taking the relationships between coal and coke quality parameters into consideration. The proposed model could provide a least cost coal blend for the desired coal blend quality with respect to ash content, volatile matter, mean maximum reflectance, coke strength and ash content, while considering different constraints, like coal availability, minimum and maximum permitted coal usage etc. Guo *et al.* (2009) proposed a model of coal blending schedule to maximize economic benefits and later applied adaptive simulated annealing GA to optimize various coal blending parameters. Jiang *et al.* (2009) employed technique for order preference by similarity to ideal solution (TOPSIS) for optimizing the coal blending process while considering four different blending strategies. Ignition temperature, volatile matter, calorific value and cost were considered as the important coal properties while identifying the optimal coal blending strategy.

Chakraborty and Chakraborty (2012) presented a multi-criteria GA approach for optimal coal blending while considering different coal grades in India. Multiple compromised optimal solutions were also provided to aid the coal blending process. Net calorific value, total moisture content, dry ash free basis volatile matter, ash percentage-based dryness and total sulphur-based dryness were identified as the blending indicators for each grade of coal. Li *et al.* (2013) proposed an inexact fuzzy programming approach for power coal blending, while considering environmental constraints for nitrogen oxide emission and nitrogen oxide decomposition in power generation facilities. Moisture value, ash content value, heating value, volatile matter, sulphur content value, cost, softening temperature and hardgrove grindability index were the input parameters to the proposed approach. Taking into consideration five coal properties, i.e. volatile matter content, heat rate, ash content, moisture content and sulphur content, Dai *et al.* (2014) developed a simulation-based fuzzy possibilistic programming model which was later solved using a direct search approach while integrating fuzzy simulation and GA techniques. It was observed that the proposed model could derive a series of coal blending schemes, identify the optimal coal blending strategies, and provide a balance between system costs and acceptable possibility levels. Santoso *et al.* (2016) optimized the low and high rank coal blending process to decrease production cost and increase plant efficiency. Finite impulse response neural network technique was adopted for model development, and principal component analysis and partial least square methods were employed for selection of the model parameters. Schellenberg *et al.* (2016) considered nine real time coal blending problems as the benchmark and solved them using GA technique. The derived results were later compared with those from a LP solver while showing the superiority of GA technique over the traditional LP method. Jin *et al.* (2017) employed a multi-objective decision-making approach based on fuzzy set theory to determine the optimal blending ratio for increased power plant economy.

Moisture content, ash content, volatile matter, fixed carbon content and calorific value of the constituent coals were adopted as the indicators to determine the optimal blending ratio.

From the review of the above-cited literature, it can be noticed that determination of the optimal composition of various coal constituents in the final blend has been a topic of immense research interest since several years, and different optimization techniques, like GA and LP have mainly been deployed to resolve this problem. In GA technique, there is almost no assurance of finding out the global optimal solution as there is a high likelihood for the solution being stuck in the local optima. For GA, a decent sized population and a large number of generations are required before achieving satisfactory solutions. In this algorithm, various control parameters, such as cross-over probability, mutation probability and elitism percentage, need to be also fine-tuned based on trial and error method. On the other hand, LP, being an iterative-based optimization tool, takes a large number of iterations before providing the optimal solution. There are also several limitations for the application of LP, like it requires the objective function and constraints to be expressed in linear form, it can only solve single objective problems, it does not consider change and evolution of the decision variables, it does not provide global optimal solution etc.

2.2 Application of PROMETHEE-GAIA method

The PROMETHEE method combined with GAIA technique was introduced by Brans *et al.* (Brans and Vincke, 1985; Brans and Mareschal, 1992) for solving multi-criteria decision-making problems. Because of numerous advantages of PROMETHEE method, easy computational procedure, comprehensiveness, ability to support group-level decision-making for debate and consensus building, capability to deal with both qualitative and quantitative criteria, capacity to tackle uncertain and fuzzy information etc., it has already found wide ranging applications in various domains of engineering and management (Behzadian *et al.*, 2010), such as environment management, hydrology and water management, business and financial management (Basilio *et al.*, 2018), logistics and transportation, lean manufacturing and assembly (Anand and Kodali, 2008) and energy management.

Wang *et al.* (2006) integrated PROMETHEE, GAIA and analytic hierarchy process (AHP) methods for solving decision-making problems in a vendor selection process. Prvulovic *et al.* (2011) applied PROMETHEE and GAIA methodologies for the selection of drying paltry seeds and powder materials. Chakraborty and Karande (2012) applied PROMETHEE and GAIA approaches for selection of non-traditional machining process for a given work material and shape feature combination. Silas *et al.* (2013) developed an efficient service selection framework for pervasive environments using PROMETHEE family of methods. From the survey of the application domains of PROMETHEE and GAIA approaches, it becomes evident that they have not been employed before as an efficient multi-criteria decision-making tool for determining the optimal coal blending strategies while considering all the physical, thermal and economic factors of the constituent coals. Therefore, in this paper, a hybrid multi-criteria decision support model is proposed which aims at providing an accurate and realistic coal blending solution while identifying the optimal composition of the constituent components in a coal blend. Sensitivity analysis is also performed to study the effects of some of the important properties of the constituent coals on the final coal blend composition.

3. Methods

The PROMETHEE is a popular multi-criteria decision-making (MCDM) method which primarily aims at ranking different alternatives based on a given set of criteria/attributes

(Brans and Vincke, 1985). Over the years, several versions of PROMETHEE method have been developed, like PROMETHEE I, II, III, IV, V and VI. The PROMETHEE I method provides a partial ranking to the alternatives, whereas, PROMETHEE II gives a complete ranking to all the alternatives. The PROMETHEE III method provides an interval order emphasizing indifference, PROMETHEE IV delivers continuous sets of possible alternatives, PROMETHEE V includes segmentation constraints and PROMETHEE VI is adopted when precise weights to different criteria are not allocated. The PROMETHEE method is complemented with GAIA approach which acts as a visual decision aid to corroborate the findings of PROMETHEE method.

Suppose in a decision-making problem, there are n candidate alternatives $A\,(a_i \in A, \text{for } i = 1, 2, 3, \ldots, n)$ to be evaluated based on m possible criteria $C\left(c_j \in C, \text{for } j = 1, 2, 3, \ldots, m\right)$. Based on the outranking principle, PROMETHEE II method evaluates the dominance of one alternative over the other and then determines the rank for each of the considered alternatives. For each pair of alternatives (a, b) in the decision/evaluation matrix and for each criterion c_j, a real number $P_j(a, b)$ is defined, as given in equation (1), which determines the preference of alternative a over alternative b with respect to criterion c_j. A deviation function is introduced in equation (2), which defines how much an alternative deviates from the other alternative, considering a given criterion.

$$P_j(a,b) = F_j\left[d_j(a,b)\right] = \begin{cases} 0, & \text{if } \quad d_j(a,b) \leq q_j \\ f\left(d_j(a,b)\right), & \text{if } \; q_j < d_j(a,b) \leq p_j \\ 1, & \text{if } \quad d_j(a,b) > p_j \end{cases} \tag{1}$$

where $f[d_j(a, b)]$ is a non-decreasing preference function in the interval [0,1].

$$d_k(a,b) = c_k(a) - c_k(b) \tag{2}$$

where $c_k(a)$ and $c_k(b)$ are the quantitative evaluations of alternatives a and b with respect to criterion c_k. To evaluate the degree of preference of alternative a over alternative b with respect to a particular criterion, six different preference functions are available, i.e. usual, U-shaped, V-shaped, level, linear and Gaussian (Brans and Vincke, 1985). On the other hand, in this evaluation process, $q_k$and $p_k$are treated as the indifference and preference thresholds, respectively. It simply signifies that if the deviation is below the indifference threshold, the preference of alternative a over b is considered negligible, whereas, if the deviation is above the preference threshold, alternative a is significantly preferred over alternative b. In the decision matrix, as the performance scores of the candidate alternatives with respect to different criteria have varying dimensional units, it is always recommended to normalize the entities of this matrix so as to make them dimensionless and comparable. However, the scale for normalization is insignificant as the degree of preference always lies in the interval [0,1].

The aggregated preference indices are then calculated, as given below:

$$\begin{cases} \pi(a,b) = \sum_{j=1}^{k} w_j P_j(a,b) \\ \pi(b,a) = \sum_{j=1}^{k} w_j P_j(b,a) \end{cases} \tag{3}$$

where w_j is the weight (relative importance) of j^{th} criterion and $\sum_{j=1}^{k} w_j = 1$. Here, $\pi(a, b)$ is the degree of preference of a over b, whereas, $\pi(b, a)$ is the degree of preference of b over a. Entropy method (Qui, 2002) is usually employed for determination of the unbiased estimates of these criteria weights. The following steps are followed in the entropy method for criterion weight estimation:

- The decision matrix is first normalized using linear normalization technique such that $r_{ij} \in [0, 1]$,where r_{ij} corresponds to the normalized performance measure of i^{th} alternative with respect to j^{th} criterion.
- The entropy measure of j^{th} criterion is then calculated as: $H_j = -k\sum_{i=1}^{n} f_{ij}\ln f_{ij}$, $j = 1, 2, 3, \ldots, m$, where $f_{ij} = r_{ij}/\sum_{i=1}^{n} r_{ij}$ and $k = 1/\ln n$, and suppose when $f_{ij} = 0$, $f_{ij} \ln (f_{ij}) = 0$.
- Finally, the weight of j^{th} criterion is calculated as follows:

$$w_j = \frac{1 - H_j}{m - \sum_{j=1}^{m} H_j} \tag{4}$$

From the aggregated preference indices, two outranking flows are now defined. The positive outranking flow, as expressed in equation (5), determines the total strength of alternative a with respect to other alternatives. On the other hand, the negative outranking flow in equation (6) determines the total weakness of alternative a with respect to other alternatives. Based on these positive and negative outranking flow values, the net outranking flow is estimated to show how an alternative fares against all other alternatives, considering both its 'bonuses' (favourable criteria) and 'penals' (unfavourable criteria). The equation (7) represents the estimation of the net outranking flow value from the positive and the negative outranking flows. These net outranking flow values are finally employed to rank all the candidate alternatives from the best to the worst.

$$\varphi^{+}(a) = \frac{1}{m-1}\sum_{x\in A} \pi(a, x) \tag{5}$$

$$\varphi^{-}(a) = \frac{1}{m-1}\sum_{x\in A} \pi(x, a) \tag{6}$$

$$\varphi(a) = \varphi^{+}(a) - \varphi^{-}(a) \tag{7}$$

Subsequently, the GAIA technique acts as a visual modelling aid to complement the complete ranking of the candidate alternatives as derived using PROMETHEE II method, and it provides guidance regarding the impact analysis of the most important criterion on the decision-making process. The GAIA plane represents the projections of a set of n alternatives as a cloud of n points in an m-dimensional space (m is the number of criteria). The positions of the alternatives on this plane signify their strengths and weaknesses with respect to different criteria under consideration. With the help of appropriate principal component analysis technique, this m-dimensional space is orthogonally projected on the GAIA plane. In the developed GAIA plane, alternatives as identified to be good on a particular criterion would be oriented in the same direction of that criterion. On the other hand, alternatives which are particularly dissimilar would lie in the opposite sides of the plot (Brans and Mareschal, 1988). The longer the axis of a criterion, the more it discriminates between the considered alternatives. In the GAIA plane, criteria having similar preferences among the alternatives are oriented in the similar direction, whereas, criteria showing conflicting preferences among alternatives, would have axes in opposite directions. All these indications act as an aid to validate the results derived from PROMETHEE II method.

The PROMETHEE (an example of outranking method) is an interactive MCDM tool designed to deal with both quantitative and qualitative evaluation criteria with discrete alternatives. The performance of the alternatives can be expressed in their own dimensions. This method can also handle uncertain and fuzzy information present in a decision matrix. In PROMETHEE method, pair-wise comparison of the alternatives is basically performed so as to compute a preference function for each criterion. Based on this preference function, a preference index for alternative a over alternative b is estimated. This preference index is the measure to support the hypothesis that alternative a is preferred to alternative b. It has several advantages over the other MCDM methods, like AHP and TOPSIS. It can classify alternatives which are difficult to compare because of a trade-off relation of evaluation standards as non-comparable alternatives. Unlike AHP method, in this method, there is no need to perform a pair-wise comparison again when comparative alternatives are added or deleted. It is a straightforward method with less computational complexity. Although a partial ranking of the alternatives is only obtained in PROMETHEE I method, but PROMETHEE II can provide a complete ranking of the alternatives from the best to the worst one. It can provide information on how the final ranking changes when different decisions on weights, criteria and aggregation procedures are considered. It also supports group decision-making, as it constitutes a useful platform for debate and consensus building (Sen *et al.*, 2015). On the other hand, GAIA is a visual aid to complement the derived rank ordering and provide valuable guidance regarding the impact of the most important criterion in the decision-making process. In the GAIA plane, positions of the alternatives decide their strengths or weaknesses with respect to different criteria under consideration. Similarly, the positions of the criteria provide information about their significance in ranking of the alternatives and possibility of any conflict between them.

The PROMETHEE V method is the extension of PROMETHEE II approach while considering segmentation constraints. This method becomes quite helpful when the set of alternatives is segmented, and needs to be verified both between and within the cluster (Chakraborty *et al.*, 2018). Thus, the following objective function is formulated such that it maximizes the benefit from all the alternatives subject to different criteria constraints:

$$\mathrm{Max} \sum_{\mathrm{i=1}}^{\mathrm{n}} \varphi(a_i) X_i \tag{8}$$

where X_i are treated here as different raw coal grades considered in the blending process.

In this hybrid decision-making model, PROMETHEE II first provides the ranking of coals from different reserves with respect to the net benefits added by the individual coals. When PROMETHEE V is integrated with PROMETHEE II, it combines the net benefits of various coals into a composite benefit function, which is subsequently maximized subject to various constraints. Hence, integration of both these PROMETHEE techniques is very critical to obtain an optimal blending decision. On the other hand, GAIA is a practical visual tool, which helps in modelling the problem graphically, providing more readability and flexibility in understanding the problem in hand, and studying the effects of various evaluation criteria and decisions on the benefit function.

Figure 2 exhibits the flowchart of the proposed multi-criteria decision-making model. In this paper, coals from the mines of two major countries, i.e. India and the USA are considered, and this hybrid model is then applied to determine the optimal compositions of different coal constituents in the final blends.

4. Results

4.1 Blending of coals from India

In this example, coals received at the washery from six different collieries of a regional coal company are considered. Broadly, coal can be classified into two groups, i.e. coking and non-

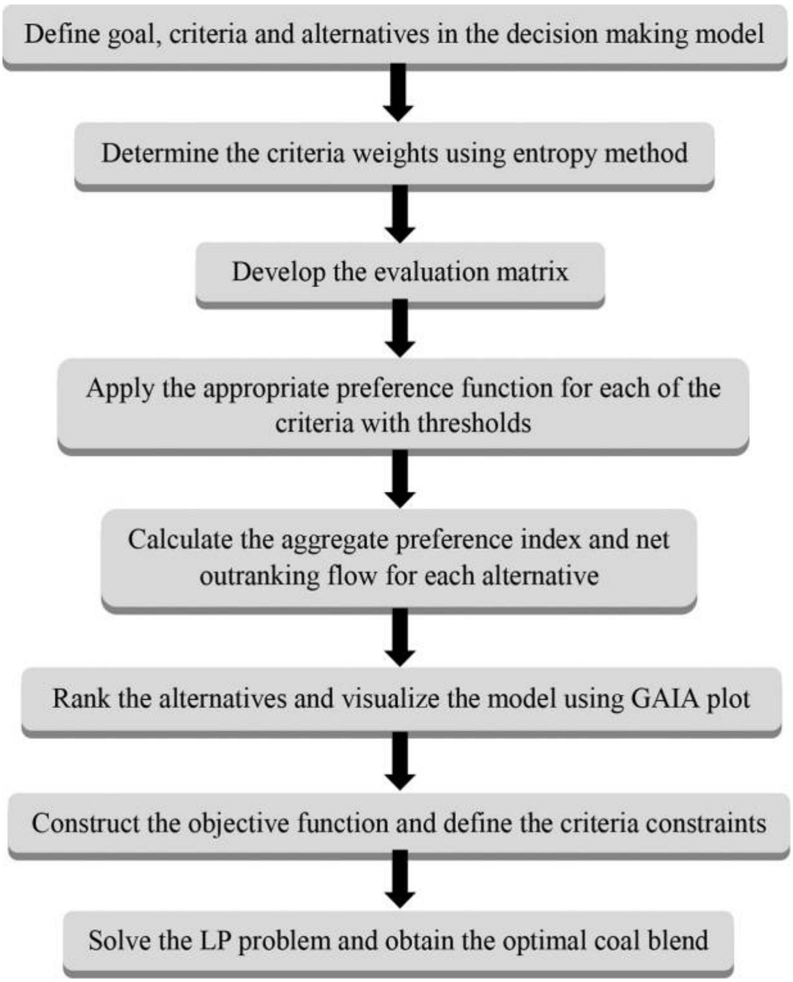

Figure 2. Flowchart of the hybrid multi-criteria decision support model

coking coals. Coking coal is sent to the washeries as it contains comparatively less ash. This coking coal is further classified into six grades, depending on their ash content, i.e. steel grades I and II, and washery grades I, II, III and IV (Chakaborty and Chakraborty, 2012). It has been reported by the past researchers that as the coal reserves having better quality of coal are limited and are also difficult to mine, the coals extracted from these reserves must be blended judiciously to have the optimal combination of all the coal properties taken under consideration. In India, BCCL (Bharat Coking Coal Limited) is the major producer of prime coking coal, and it encompasses several coal mines, as well as washeries, located mostly at Talcher (Odisha), Korba (Chhattisgarh) and Jharia (Jharkhand) area. The most notable washeries from which coal is collected after washing are located at Durgapur (West Bengal), Kargali (Jharkhand), Kathara (Bihar), West Bokaro (Jharkhand), Kedla (Jharkhand), Madhuband (Bihar), etc.

In this example, five different properties of coal are considered, i.e. input cost (C_1) (in INR/ton), calorific value (C_2) (in cal/kg), moisture content (C_3) (in per cent), ash content (C_4) (in per cent) and sulphur content (C_5) (in per cent). Here, calorific value of a particular grade of coal is the sole beneficial property always requiring its higher value, whereas, the remaining four coal properties are non-beneficial in nature preferred with their lower values. The above-mentioned criteria are chosen in such a way that they consist of both beneficial and non-beneficial properties of coal, as well as include cost factor at the same time. All these criteria chosen affect differently the overall benefit obtained from the use of the blended coal. Table I provides the detailed values of all the considered properties for six different grades of coal. This table also exhibits the information regarding the average value of each of the coal properties. To estimate the relative significance of each criterion (coal property) in the coal blending process, entropy method is employed here to determine the weight of each of the coal properties, as also given Table I. It can be revealed from this table that moisture content of coal is the most significant criterion with a priority weight of 0.2267, followed by ash content, sulphur content, input cost and calorific value in order of their preference.

Now, while using PROMETHEE II method and based on the usual preference function, the net outranking flows for all the six coal grades are calculated and they are subsequently ranked, as shown in Table II. It can be observed from this table that steel grade I (ST1) and washery grade II (W2) occupy the top two positions in the derived ranking list, and they are the major contributors in the final blend taking into consideration the coals extracted from different mines in India. This same observation can well be validated from the GAIA plot and PROMETHEE rainbow diagram as shown in Figures 3 and 4, respectively. Based on these GAIA plot and PROMETHEE rainbow diagram, the following conclusions can be drawn:

	Properties (Criteria)				
Alternative	Input cost C_1	Calorific value C_2	Moisture content C_3	Ash content C_4	Sulphur content C_5
Steel grade I (ST1)	2316.2	3900	30.5	13.5	0.56
Steel grade II (ST2)	1996.2	3100	33.6	16.5	0.78
Washery grade I (W1)	1714.2	3800	32.4	19.5	0.7
Washery grade II (W2)	1403.37	3500	29.7	22.5	0.5
Washery grade III (W3)	1118.4	2800	31	25.5	0.45
Washery grade IV (W4)	999.2	3500	34.2	28.5	0.34
Average	1591.26	3433.33	31.9	21	0.55
Weight	0.1920	0.1758	0.2267	0.2059	0.1995

Table I. Properties of different coal grades for Example 1

- Coal property C_3, i.e. moisture content is the most significant criterion having the longest axis in the GAIA plot and it has the maximum power in discriminating the six considered Indian coal grades.
- Coal grades ST1 and W2 are oriented in the same direction of the decision axis (shown in red colour in the GAIA plane), which signify that they are the best options among all the candidate alternatives.
- Coal grade ST1 has the maximum distance from the origin in the direction of the decision axis. Hence, it is the best performing alternative.
- Coal grade W2 has four 'bonus' properties (C_1, C_2, C_3 and C_5). It is only lagging behind with respect to coal property C_4 (ash content).
- Coal grade ST1 has three 'bonus' properties (C_2, C_3 and C_4) and two 'penal' properties (C_1 and C_5).
- Coal grade ST2 occupies the last position in the ranking list, having only one property in its favour, i.e. it has moderately low ash content.

Hence, the integrated approach of PROMETHEE and GAIA methods helps in identifying the most suitable constituent grades of coal in the final blend taking into consideration the

Rank	Alternative	Net outranking flow
1	Steel grade I (ST1)	0.2858
2	Washery grade II (W2)	0.2638
3	Washery grade III (W3)	−0.0191
4	Washery grade IV (W4)	−0.0411
5	Washery grade I (W1)	−0.0568
6	Steel grade II (ST2)	−0.4327

Table II. Complete ranking of the alternative coal grades in Example 1

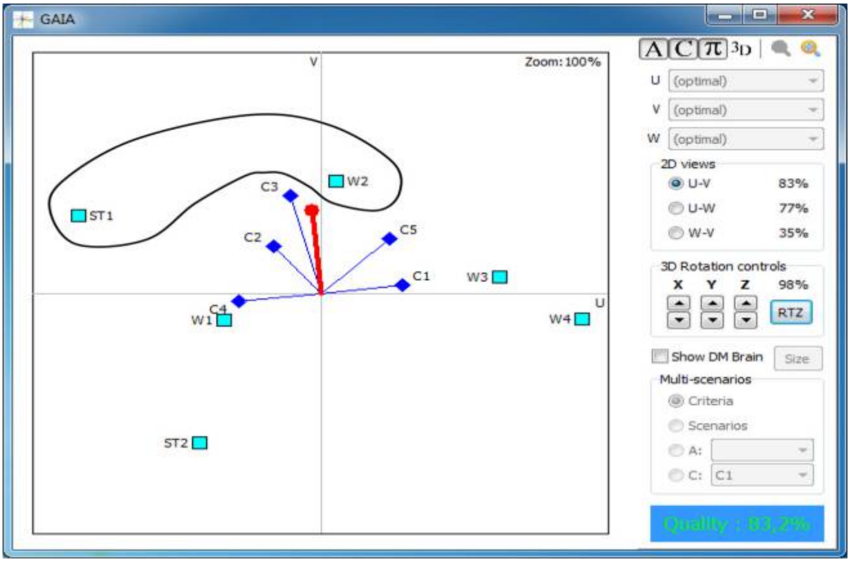

Figure 3. Developed GAIA plane for Example 1

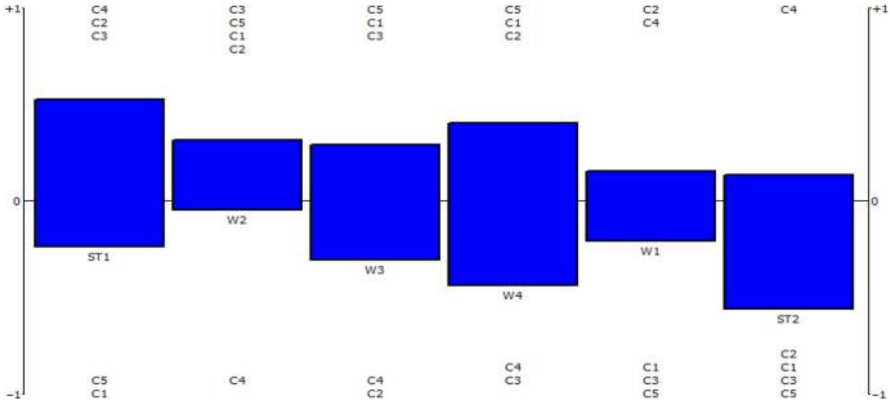

Figure 4.
PROMETHEE rainbow diagram for Example 1

strengths and weaknesses of all the six coal grades. As observed, it is almost impossible to find out a particular grade of coal having all of its properties as "bonus". Thus, PROMETHEE V is now employed here to solve this Indian coal blending problem to obtain an optimal mix while satisfying a given set of criteria constraints. This method determines the composition of the preselected coal constituents in the final blend. To solve this coal blending problem, an LP model is developed based on equation (8) subjected to various constraints associated with the achievement of different coal property values. In these constraints, the right hand side constants are the average values of different coal properties. On the other hand, the constants in the objective function equation are the derived net outranking flow values for the six coal grades. This LP problem is subsequently solved using MATLAB (R2011b) and the derived results are shown in Table III.

$$\textit{Maximize } Z = 0.2858X_1 - 0.4327X_2 - 0.0568X_3 + 0.2638X_4 - 0.0191X_5 - 0.0411X_6 \quad (9)$$

Subject to

$$2316.2X_1 + 1996.2X_2 + 1714.2X_3 + 1403.37X_4 + 1118.4X_5 + 999.2X_6 \leq 1591.26 \text{ (input cost)}$$

$$3900X_1 + 3100X_2 + 3800X_3 + 3500X_4 + 2800X_5 + 3500X_6 \geq 3433.33 \text{ (calorific value)}$$

$$30.5X_1 + 33.6X_2 + 32.4X_3 + 29.7X_4 + 31.0X_5 + 34.2X_6 \leq 31.9 \text{ (moisture content)}$$

$$13.5X_1 + 16.5X_2 + 19.5X_3 + 22.5X_4 + 25.5X_5 + 28.5X_6 \leq 21 \text{ (ash content)}$$

$$0.56X_1 + 0.78X_2 + 0.70X_3 + 0.50X_4 + 0.45X_5 + 0.34X_6 \leq 0.55 \text{ (sulphur content)}$$

$$X_1 + X_2 + X_3 + X_4 + X_5 + X_6 = 1, X_i \geq 0 \text{ (for } i = 1, 2, \ldots, 6)$$

Table III.
Optimal solution for Example 1

Alternative (Coal blend constituent)	Percentage composition
Steel grade I (ST1)	0.2058
Steel grade II (ST2)	0
Washery grade I (W1)	0
Washery grade II (W2)	0.7942
Washery grade III (W3)	0
Washery grade IV (W4)	0
Objective function value	0.2683

The results derived in Table III indicate that in this blending process for the Indian coals, the final blend contains 79.42 per cent (approximately 80 per cent) of washery grade II (W2) and 20.58 per cent (approximately 20 per cent) of steel grade I (ST1). The higher percentage composition of W2 coal in the final blend can be attributed to the fact that it has the least amount of moisture content, moderately low input cost, comparatively low levels of ash content and sulphur content, and a high calorific value. It is also worthwhile to mention here that the moisture content property against which coal grade W2 is extremely strong, is already deemed to be most significant criterion in this coal blending process. The final coal blend also contains approximately 20 per cent ST1 coal grade, owing to its maximum calorific value. It has the minimum ash content, but also has the highest input cost. In the final blend, the average values of different coal properties are estimated as input cost =1591 INR/ton, ash content = 20.64 per cent, calorific value = 3582.3 cal/g, sulphur content = 0.51 per cent and moisture content = 29.86 per cent.

To better understand the economic impact of this coal blending process, sensitivity analysis is performed to show the effects of changing values of input cost of raw coal on the final blend composition, while keeping the other coal properties constant. The results of this sensitivity analysis are shown in Figure 5. It can be observed from this figure that below the average input cost at ~1560 INR, it is almost impossible to obtain an optimal blend composition satisfying all the considered constraints. It can also be noticed that the more the bound on coal input cost is relaxed, more would be the participation of ST1 coal grade in the final blend (its amount increases from 17 per cent to 91 per cent in the blend). It can be revealed from Table I that except the input cost, coal grade ST1 has favourable values of calorific value, moisture content and ash content as compared to coal grade W2. Both of them have almost comparable sulphur content. Thus, when the economic constraint is released, ST1 would likely replace W2 in the final coal blend. Keeping in mind the scarcity of better coal reserves in India as well as other economic considerations, it is always advisable to take the help of this hybrid multi-criteria decision-making model in identifying the composition of the constituent coal grades in the final blend.

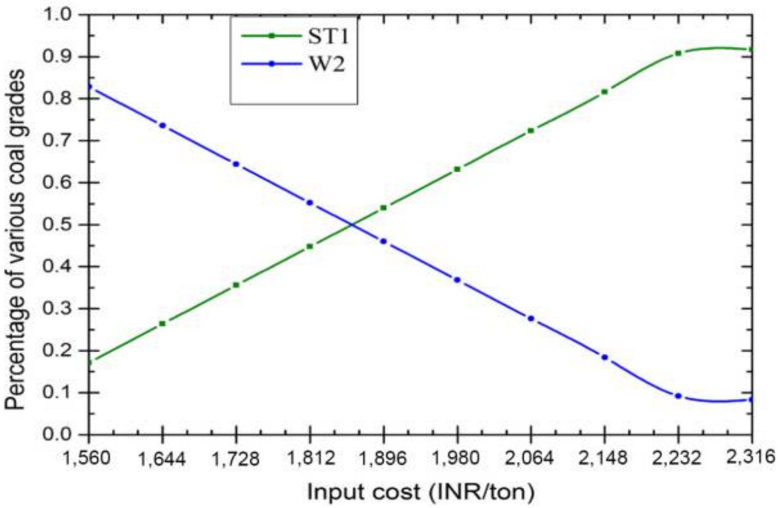

Figure 5.
Sensitivity analysis with respect to input cost in Example 1

4.2 Blending of coals from the USA

In this example, raw coals from 11 different coal mines in the USA are considered to determine the optimal coal blending strategy. The relative performance of these coals is evaluated with respect to five different coal properties, i.e. ash content (C_1) (in per cent), sulphur content (C_2) (in per cent), maximum reflectance (C_3), dilatation (C_4) and purchase price (C_5) (in USD/ton). The values of these properties are provided in Table IV, along with related demographic information of the considered coals. Amongst these five properties of raw coal, maximum reflectance and dilation are the beneficial criteria and the remaining three are non-beneficial criteria. The last two rows of Table IV respectively represent the average and weight of each of the five coal properties. In this example, maximum reflectance has the highest significance (weight of 0.4071), followed by purchase price of coal (weight of 0.2439). It can also be noticed that in comparison to the Indian coals, coals from the American mines have relatively higher sulphur content, but very low ash content. Using PROMETHEE II method, the corresponding net outranking flow values for all the coal alternatives are now estimated, based on which they are also ranked, as exhibited in Table V.

From the results derived from the PROMETHEE II method-based analysis, it can be observed that in this coal blending problem, the top four positions of the ranking list are occupied by Rowland (A_5), Masco (A_{10}), Beartrice (A_3) and Icc Type B (A_6) alternatives. The corresponding GAIA plot and PROMETHEE rainbow diagram are shown in Figures 6 and 7, respectively. From these two figures, the following observations can be inferred:

- C_3 (maximum reflectance) is the most significant criterion having the maximum axis length.
- Coal alternatives A_5 and A_{10} are the closest to the decision axis, and they too share the same three "bonus" criteria (C_3, C_4 and C_5) and two "penal" criteria (C_1 and C_2).
- Alternative A_3 is in the third position of the ranking list with three "bonus" (C_1, C_2 and C_3) and two "penal" (C_4 and C_5) criteria.
- Criteria C_1 and C_2, and criteria C_4 and C_5 are oriented in opposite directions in the GAIA plot, and they have almost the similar preferences in evaluating the performance of the coal alternatives.
- Coal alternative Gilbert (A_7) occupies the last position in the derived ranking list, having no "bonus" property in its favour.

	Properties (Criteria)				
Alternative	Ash content C1	Sulphur content C2	Maximum reflectance C3	Dilatation C4	Price C5
Keystone (McDowell, West Virginia) (A_1)	5.5	0.8	1.64	35	72
Itmann (Wyoming, West Virginia) (A_2)	5.5	0.8	1.52	55	70.6
Beartrice (Buchannan, Virginia) (A_3)	4.5	0.7	1.66	44	72.21
Pittston (Luzerne, Pennsylvania) (A_4)	7	0.7	1.04	132	69.8
Rowland (Raleigh, West Virginia) (A_5)	6.5	0.8	1.3	215	60.5
Icc Type B (Montana) (A_6)	4.25	0.8	0.91	170	54.5
Gilbert (Mingo, West Virginia) (A_7)	9.5	0.8	0.9	130	64.48
Sprague (Lincoln, Washington) (A_8)	6	0.8	0.9	130	60.72
Kellerman (Tuscaloosa, Alabama) (A_9)	5.5	0.8	0.94	152	57
Masco (Kentucky) (A_{10})	6.5	0.9	1.1	150	53
Harman (Buchannan, Virginia) (A_{11})	6	0.8	1	145	60
Average	6.07	0.79	1.17	123.45	63.16
Weight	0.0808	0.0978	0.4071	0.1703	0.2439

Table IV.
Properties of different coals for Example 2

Thus, the hybrid approach integrating PROMETHEE II and GAIA methods provides a fair idea about the candidate constituents in the final coal blend with the help of complete ranking of the alternatives and developed visual aid. However, there is no single coal alternative identified having all of its five properties as 'bonus'. This compels for the application of PROMETHEE V method which helps in segmentation while identifying the optimal composition of the constituent coals from the mines of the USA in the final blend subjected to a set of constraints imposed based on the fulfilment of the considered coal properties. For this, the following LP problem is developed and subsequently solved. The derived results are provided in Table VI.

$$\textit{Maximize}\ Z = -0.0172X_1 + 0.0183X_2 + 0.1796X_3 - 0.0742X_4 + 0.3318X_5 + 0.1581X_6 - 0.5569X_7 - 0.4354X_8 + 0.1082X_9 + 0.2553X_{10} + 0.0323X_{11} \tag{10}$$

Subject to

$5.5X_1 + 5.5X_2 + 4.5X_3 + 7.0X_4 + 6.5X_5 + 4.25X_6 + 9.5X_7 + 6.0X_8 + 5.5X_9 + 6.5X_{10} + 6.0X_{11} \leq 6.07$ (ash content)

$0.8X_1 + 0.8X_2 + 0.7X_3 + 0.7X_4 + 0.8X_5 + 0.8X_6 + 0.8X_7 + 0.8X_8 + 0.8X_9 + 0.9X_{10} + 0.8X_{11} \leq 0.79$ (sulphur content)

$1.64X_1 + 1.52X_2 + 1.66X_3 + 1.04X_4 + 1.30X_5 + 0.91X_6 + 0.9X_7 + 0.9X_8 + 0.94X_9 + 1.1X_{10} + 1X_{11} \geq 1.17$ (maximum reflectance)

$35X_1 + 55X_2 + 44X_3 + 132X_4 + 215X_5 + 170X_6 + 130X_7 + 130X_8 + 152X_9 + 150X_{10} + 145X_{11} \leq 123.45$ (dilatation)

$72X_1 + 70.6X_2 + 72.21X_3 + 69.8X_4 + 60.5X_5 + 54.5X_6 + 64.48X_7 + 60.72X_8 + 57X_9 + 53X_{10} + 60X_{11} \leq 63.16$ (price)

$X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8 + X_9 + X_{10} + X_{11} = 1, X_i \geq 0$ (for $i = 1, 2, \ldots, 11$)

It is observed from the results of Table VI that the final blend consists of coals from the mines of Beartrice (A_3) and Rowland (A_5) with a contribution of 21.6 per cent and 78.4 per cent respectively. This can be owed to the fact that coal from the mines of Rowland has the maximum dilatation value (215) and reasonable price (US$60.5/ton), whereas, coal from the mines of Beartrice has comparatively high price (approximately US$72/ton), very low dilatation (44), highest maximum reflectance (1.66) and lowest ash content (4.5 per cent) values. Thus, a judicious mixture of the coals from the mines of Beartrice (A_3) and Rowland (A_5) can attain all the properties as desired in the blending process. The values of different coal properties in the final blend are estimated as ash content = 6.0682 per cent, sulphur content = 0.7784 per cent, maximum reflectance = 1.378, dilatation = 178.08 and purchase price = 63.03 USD/ton.

Rank	Alternative	Net outranking flow
1	Rowland (A_5)	0.3318
2	Masco (A_{10})	0.2553
3	Beartrice (A_3)	0.1796
4	Icc Type B (A_6)	0.1581
5	Kellerman (A_9)	0.1082
6	Harman (A_{11})	0.0323
7	Itmann (A_2)	0.0183
8	Keystone (A_1)	−0.0172
9	Pittston (A_4)	−0.0742
10	Sprague (A_8)	−0.4354
11	Gilbert (A_7)	−0.5569

Table V.
Net outranking flows and ranking of the alternatives in Example 2

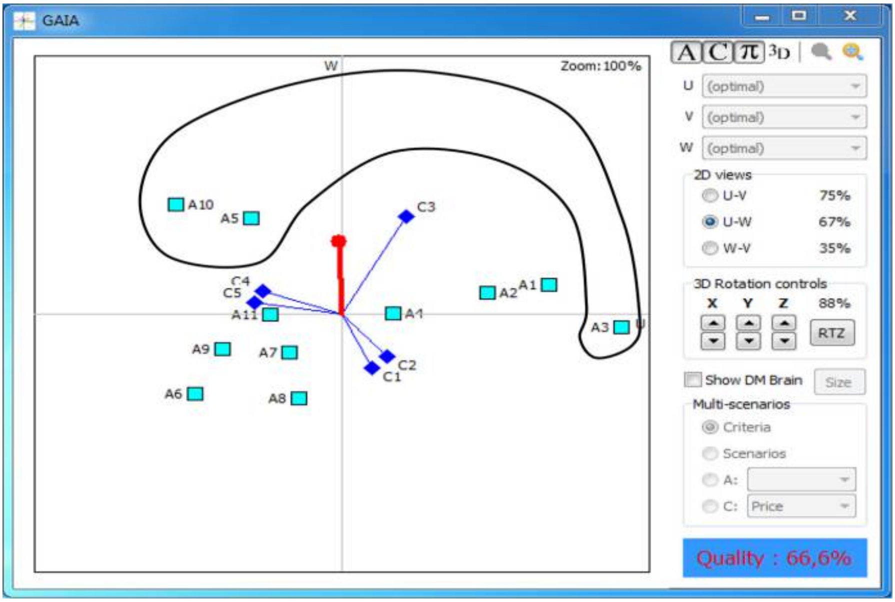

Figure 6.
Developed GAIA plot for Example 2

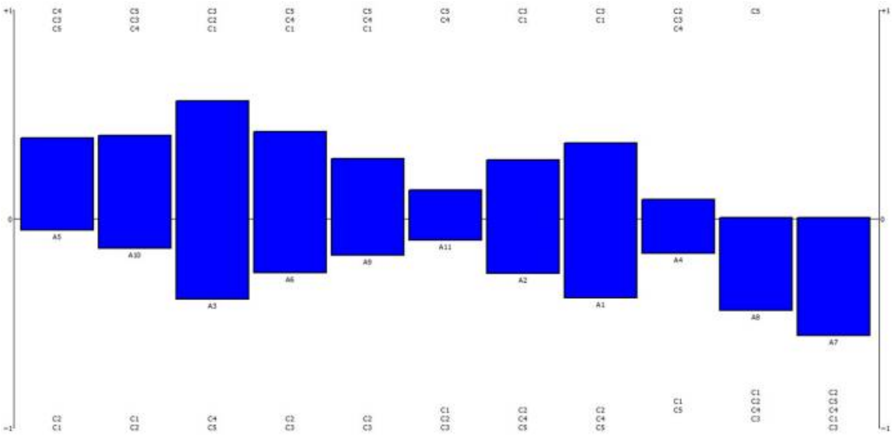

Figure 7.
PROMETHEE rainbow diagram for Example 2

Now, to study the effects of raw coal purchase price and ash content on the compositions of the constituent coals in the final blend, sensitivity analysis studies are subsequently performed. The results of these sensitivity analyses are depicted in Figures 8 and 9. It can be observed from these two figures that lowering the average purchase price below 59.12 USD/ton or lowering the target ash content below 4.34 per cent leads to an infeasible solution, i.e. no optimal coal mix is obtained. It can also be noted that when the purchase price is lowered below the value of ~63.03 USD/ton, a new coal mix is emerged where coal alternative Icc Type B has a significant contribution in the blend. It can be affiliated to the fact that the coal alternative Icc Type B has the second minimum purchase price. This fact can also be evident

Alternatives (Coal blend constituent)	Percentage composition
Keystone (A_1)	0
Itmann (A_2)	0
Beartrice (A_3)	0.2159
Pittston (A_4)	0
Rowland (A_5)	0.7841
Icc Type B (A_6)	0
Gilbert (A_7)	0
Sprague (A_8)	0
Kellerman (A_9)	0
Masco (A_{10})	0
Harman (A_{11})	0
Objective function value	0.2989

Table VI. Optimum solution for Example 2

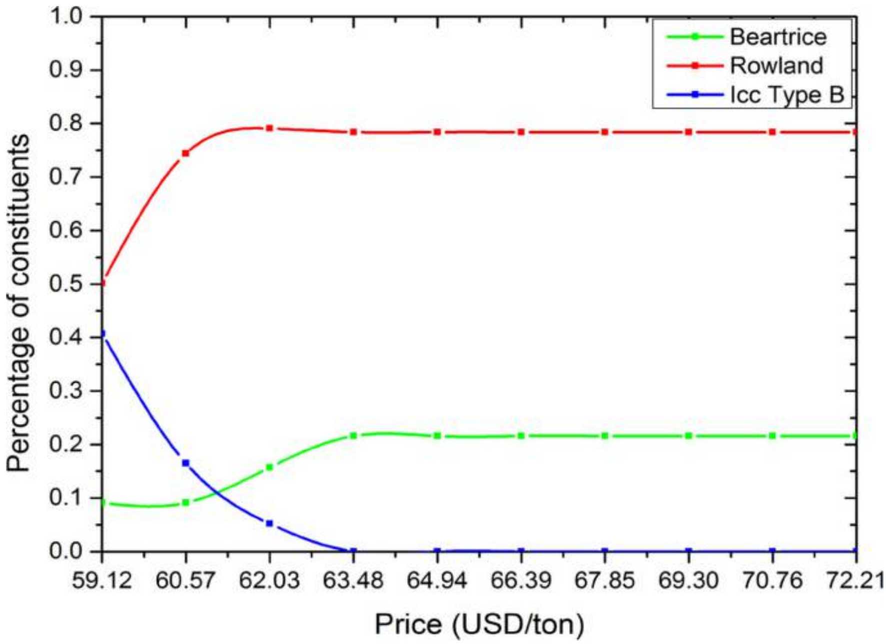

Figure 8. Sensitivity analysis with respect to purchase price in Example 2

from the PROMETHEE rainbow diagram of Figure 7 where coal alternative A_6 (Icc Type B) has the purchase price as its top most "bonus" property. It is also interesting to notice that although the coal alternative A_{10} (Masco) has the second rank with the least purchase price; it is not identified as a constituent in the final blend because it has the maximum ash content and sulphur content values. After the purchase price of approximately US$63.03/ton, coal alternatives Beartrice and Rowland become the steady contributors in the coal mix. A similar trend can be observed from the sensitivity analysis plot for ash content in Figure 9. Below the target ash content level of 6.06 per cent, coal alternative Icc Type B occupies a position in the optimal coal blend. This can be supported by the fact that it has the least ash content (approximately 4.25 per cent), closely followed by Beartrice (approximately 4.5 per

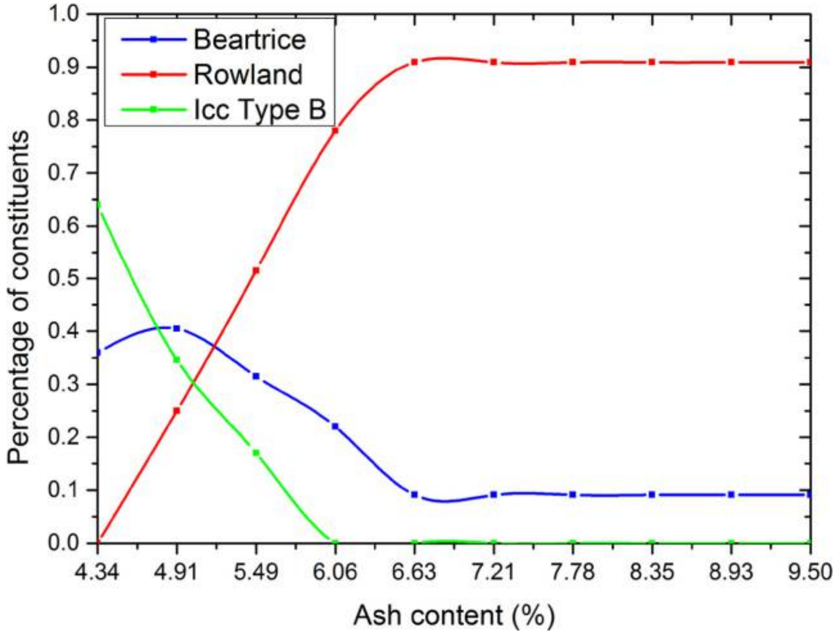

Figure 9.
Sensitivity analysis with respect to ash content in Example 2

cent). However, beyond the ash content level of 6.06 per cent, Icc Type B does not feature in the optimal coal blend because it has almost the worst value for maximum reflectance (0.91), which is also the most important criterion in this coal blending problem. So, it can be propounded that although lower purchase price or lower ash content can be achieved, but at the cost of a relatively lower ranked coal with lower maximum reflectance value.

5. Discussions

It has become evident from the literature survey that all the previous approaches proposed for determining the optimal coal blending strategies have considered either a single objective (like cost or sulphur emission) or multiple objectives. However, in this combined PROMETHEE-GAIA-based approach, a new decision model is developed which would decide the net benefit that a constituent coal can provide to the whole blend, and different constituents are thus ranked based on these net benefits. This helps the concerned decision makers to have a clear idea about which of the constituents would be more beneficial for the blend (while considering several metallurgical, as well as economical criteria). Furthermore, to provide an optimal blending decision, an LP model is formulated having a single objective, i.e. to maximize the benefit out of all the different constituents in the final blend taken together. For simplicity, linearized constraints are considered for different coal properties in the LP model. This model would guarantee a global optimal solution. Further analysis is also performed to observe the sensitivity of the objective function with respect to different criteria bounds. It would help the decision makers to be flexible enough in their choices depending on the changing criteria constraints. The GAIA method, integrated with PROMETHEE technique, would also provide a visual decision aid to understand the positions of different coal constituents with respect to the objective function and constraints.

One of the main disadvantages of this adopted model is that it assumes linearized constraints with no correlation between different properties of the constituent coals considered in the blend. This assumption simplifies the model to provide a good enough blend decision to the decision makers in least time.

The topic of this paper mainly focuses on solving one of the pressing problems in steel production industry, i.e. determination of an optimal coal blending strategy that would result in better utilization of coal at a reasonable price. The hybrid decision-making model integrating PROMETHEE and GAIA approaches becomes successful in providing the optimal blend composition, keeping in mind the related economical constraints. Based on the solutions from this hybrid model, the engineers working in steel plants would have direct benefits. This new approach not only provides an optimal coal blending strategy but also generates alternative optimal compositions of the constituent coals in the final blend that would result from relaxing some of the considered constraints. This allows the concerned engineers enough flexibility in choosing alternative blending strategies when they can relax some constraints. One of the major impacts of this model would be in reducing the pollution rate, by choosing a composition that would emit as minimum as possible greenhouse gases after combustion of constituent coals. As economical factors are also considered in this model, the final composition provides a more realistic solution, because making profit is always one of the major targets of any organization.

Although, in this paper, the hybrid model accommodates the economical constraints, there are several other real factors which can be considered in the model in near future. Availability of resources is one of those factors that poses a challenge to the blending decision. As coal takes millions of years to develop and there is a limited amount of it, it is considered as a non-renewable source of energy. Moreover, shortage of higher grade of coal as compared to abundance of lower grade of coal introduces a complexity to the decision-making problem. Hence, sustainability of resources, i.e. using the most out of the available and at the same time, conserve for the coming generations, are the important questions needed to be answered in future research work.

6. Conclusions

In this paper, a hybrid multi-criteria decision-making model is framed while simultaneously extracting the benefits from PROMETHEE II and V methods, and GAIA approach. The PROMETHEE II provides a complete ranking of different coal alternatives based on the considered coal properties, whereas, GAIA method provides a visual decision aid while supporting the results derived from PROMETHEE II method. It also identifies the relative strengths and weaknesses of the candidate alternatives with respect to different coal properties. Finally, PROMETHEE V method determines the optimal composition of the constituent coals in the final blend while satisfying the attainment of different criteria/properties. From the derived solutions, it can be concluded that the proposed model can provide quite economical decisions regarding the compositions of the optimal coal blends while maintaining good output quality of the final mixes. The GAIA plane and PROMETHEE rainbow diagram also guide the decision-making process in identifying the "bonus" and "penal" properties for each of the coal alternatives. The sensitivity analyses also show the effects of variations of different coal properties on the compositions of the final blends. To provide more flexibility to the concerned engineers about the blending ratio, these analyses guide them in the decision-making process while judging the impacts of different constraints on the optimal coal blend. As this model takes into account the purchase price of coals from different reserves, it is always expected to provide more realistic solutions. Thus, it would be beneficial to deploy this decision-making model to different blending optimization problems in other spheres of manufacturing industries. There are also certain limitations in this model which may be the topic of future research work. For example, apart from the economic consideration, there is also another factor which highly affects the blending ratio, i.e. availability of resources. Given the increasing consumption of available resources from different coal mines, it would be more practical to judiciously use those resources to extract maximum benefit, while keeping the sustainability factor in mind. Therefore, the application of this model can be extended to further accommodate factors, like availability of coals and sustainability issues in future studies.

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