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The problem of ranking CO_2 abatement measures: A methodological proposal

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ABSTRACT

Marginal Abatement Cost curves are considered a standard tool for analysing the impacts of mitigation measures and are one of the most used methodologies for evaluating abatement options by comparing their cost-effectiveness. Nevertheless some discrepancies regarding their construction and interpretation arose in the last few years. In this paper, we analyse the methods found in the literature for evaluating and ranking abatement measures, identify unsolved issues and propose three alternative methods. The first method, Gain Maximizing (GM), supports an environmentalist attitude and performs a direct comparison of measures with both negative and positive costs. The second, Extended MAC method (EMAC), considers an economically driven point of view, weighting the negative cost options according to its economic savings over its reduction potential. The third is a Balanced Ordering Method (BOM), consisting in a linear weighted combination of two discretional seed methods, which allows decision makers to create new rankings adjustable to a specific greenhouse gases policy, whether it is fully or partially driven by economical or environmental positions. Finally, the authors propose a methodology for comparing methods based on their Kendal tau distance to the benchmarks considered relevant in the decision making process (economical profit and environmental benefit).

1. Introduction

Decision makers face several difficulties in finding appropriate solutions to greenhouse gas (GHG) mitigation without imposing heavy economic burdens on society in the context of limited budgets and divergent interests of environmentalists or economically driven actors. Policy makers in developed and developing countries around the world are substantially committed to the reduction of carbon emissions over the coming years, since the global energy use and its corresponding emissions will grow.

Policy makers, together with governments, make use of models and tools such as Marginal Abatement Cost curves (MACC or MAC curves) to negotiate with emitting sectors and environmentalists the developing of route maps for emissions reductions with limited budgets (Moran et al., 2008). These help them to identify policies and appropriate instruments to justify investment decisions (Kesicki, 2013) and to demonstrate how much abatement an economy can afford and the area to focus on in order to achieve target emission reductions (Vogt-Schilb & Hallegatte, 2014).

MAC curves can be defined as a graphical ordered representation of energy measures, which can be used to rank these measures in terms of their specific marginal cost of reducing GHG emissions (one tonne of equivalent CO_2), or the extra cost added to the total cost for a unit of output (Paulson, 1948). More recently, Kesicki and Strachan (2011) defined a MAC curve as a "*graph that indicates the cost, usually in \$ or another currency per tonne of CO_2, associated with the last unit of emission abated for varying amounts of emission reductions (generally in million tonnes of CO_2)*".

In the challenge of designing decarbonizing policies economically efficient, policy makers rank and prioritise the available abatement measures with regard the costs and mitigation potentials by applying MAC curves. MACCs show the economic and technological feasibility of climate change mitigation, relating the marginal cost of emission abatement for varied technologic options. In other words, MACCs shows the economic and technological feasibility of climate change mitigation, by relating the marginal cost of emission abatement for varying amounts of emission reduction,

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Notations

The following concepts, symbols and acronyms are used in this article:

ΔB_m	Economic benefit generated by the energy savings for a measure m
ΔC_m	Associated net present value associated to a measure m
ΔE_m	GHG abatement potential associated to a measure m
$BOM^{\alpha}(\mu_1, \mu_2)(m)$	Balanced Ordering Method for methods $\mu 1$ and $\mu 2$, and a balanceα
$Cost_m$	Total cost of the measure m ($Cost_m = \Delta C_m - \Delta B_m$)
ENV	Environmentalist benchmark
GHG	Greenhouse gases
$GM(\varepsilon)$	Gain maximizing method being ε a very small value
$GM(1)$	Gain maximizing method being ε=1.
GM_m	Gain value for a measure m
GRE	Greedy benchmark
EMAC	Extended MAC method
$EMAC_m$	Extended MAC value for a measure m
MACC	Marginal Abatement Costs Curve
MAC_m	Marginal cost of abating a tonne of CO_2 for a measure m
m	Measure
NPV	Net present value
$sign(x)$	Sign of x
τ_{MAC}	Set of ordered measures applying method MAC
τ_{Ward}	Set of ordered measures applying method Ward
τ_{Taylor}	Set of ordered measures applying method Taylor
$\tau_{GM(\varepsilon)}$	Set of ordered measures applying method GM(ε) being ε a very small value
$\tau_{GM(1)}$	Set of ordered measures applying method GM(ε) being $\varepsilon = 1$
τ_{EMAC}	Set of ordered measures applying method Emac
$K\left(\tau_{\mu_1}, \tau_{\mu_2}\right)$	Kendall tau distance between methods μ_1 and μ_2

becoming a standard tool to illustrate the economics of climate change mitigation as a tool for policy analysis (Kesicki & Ekins, 2012; Kesicki, 2012).

MAC curves are considered a standard tool, especially for analysing the impacts of the Kyoto Protocol (Contreras, 2016; Ellerman, Jacoby, & Decaux, 1998; Klepper & Peterson, 2006). Several applications are found in agriculture (Bockel, Sutter, Touchemoulin, & Jönsson, 2012; MacLeod et al., 2010; Moran et al., 2008; Moran et al., 2010), shipping (Magnus, Tore, Peter, Øyvind, & Stig, 2011), building (Mortimer, Ashley, Moody, Rix, & Moss, 1998; Ibn-Mohammed, Greenough, Taylor, Ozawa-Meida, & Acquaye, 2013; Kuusk, Kalamees, & Maivel, 2014), the cement industry (Szabó, Hidalgo, Císcar, Soria, & Russ, 2003), watercycle (van Odijk, Mol, Harmsen, Struker, & Jacobs,, 2012), transport (Kok & Annema, 2010), non-CO_2 greenhouse gases (Gallaher, Petrusa, & Delhotal, 2005) and policy making (Kesicki, 2010; Morthorst, 1994; Toke & Taylor, 2007).

Although MAC curves are proven to be extremely efficient in communicating results regarding the economic implications of climate mitigation by reporting the cost and potential of a list of mitigation measures (Vogt-Schilb & Hallegatte, 2014), some discrepancies arose relating to the construction and interpretation of MAC curves in recent years (Ackerman & Bueno, 2011; Kesicki & Ekins, 2012; Kesicki & Strachan, 2011; Kok & Annema, 2010). Kesicki and Strachan (2011) and Kesicki and Ekins (2012) uphold that MAC curves are a useful tool but its simplistic approach is misleading, possibly causing biased decision-making. Kesicki and Ekins (2012) categorise these shortcomings into those that are general faults of MAC curves and those that are specific to the MACC approach. The general shortcomings consider the inability to capture the intersectoral, intertemporal and macroeconomic interactions, as well as the wider social implications related to climate change mitigation. The MACC specific weaknesses include the lack of full disclosure behind the calculations that can lead to problems when defining an emission baseline as MAC curves cannot display those interactions.

Ackerman and Bueno (2011) stated that abatements with negative net costs are controversial among economists and problematic for modelling purposes and avoided this issue by assuming a near-zero but positive cost on all negative-cost abatements. In a similar way, Kesicki and Ekins (2012) disputed the existence of negative abatement costs, which produce a return on investment (with the so-called win-win measures). These authors argue that those results could be explained by an insufficiently extensive cost definition, non-financial barriers to implementation or inconsistent discount rates and consequently these costs are not compatible with an efficient market.

Taylor (2012) and Ward (2014) dealt with the flaw in the cost-effectiveness calculation that generates the MAC curves relating to negative costs. Taylor (2012) did not take into account the arguments of Ackerman and Bueno (2011) and Kesicki and Ekins (2012) but instead focused on the mathematical treatment and accuracy of the ranking of options that generate income (negative cost). The problem is that MAC curves use the same criteria for ranking abatement measures with positive and negative costs. The resulting rank applying traditional MACC for the negative side favours measures that produce low emission reductions over options with the same negative cost but greater CO_2 reduction potential (Taylor, 2012; Ward, 2014), even when assuming properly calculated costs resulting in negative results. This rank is therefore unreliable.

Taylor (2012) was the first author to propose a solution for this issue. He devised an alternative partial ranking method using a Pareto front for measures with negative costs and uses MACC to measure the positive ones. Taylorís model ranks measures with positive and negative costs using different approaches, which could provide discontinuous results and often ranking draws that are ambiguous and open for subjective selection. Ward (2014) proposed to plot a function that is more directly related to the benefit (in terms of avoided CO_2), taking a range of values or simply plotting the net benefit of each measure. This procedure consists of adopting measures of financial benefit, added to the emissions avoided and multiplied by an assumed value of avoided emissions.

All previous ranking methods do not take into account the interests of decision makers, regardless of whether they are fully or partially driven by economical or environmental positions. In order to partially fill this gap, we discuss three novel methods for evaluating and raking abatement measures. These are plotted in a graphical representation similar to the MAC curve, which produces continuous results for positive and negative costs.

In Section 2 we describe the fundamentals of the MACC method and its anomalies. Section 3 briefly presents the alternative ranking methods for negative cost available in the literature. In the Section 4, the authors propose two new methods: the first called The Gain Maximizing method, designed with an environmental focus, and the second called the Extended MACC method, designed with a greedy driven point of view. The Section 5 shows a comparison and discussion of the analysed ranking methods. The Section 6 presents the Balanced Ordering Method that gathers the goodness of the exposed approaches as a weighted combination of any of the exposed methods (that will work as seed methods), enabling decision makers to represent their specific interests in the ranking of GHG abatement measures. A case study for Colombia is presented

Table 1
Ordered Set for negative cost measures applying traditional *MAC*.

Measure	MAC_m	τ_{MAC}
A	−514.41	1
B	−384.11	2
C	−356.54	3
D	−191.35	4
E	−174.87	5
F	−158.19	6
G	−157.16	7
H	−142.19	8
ZZ	−99.00	9
I	−98.29	10
J	−91.24	11
K	−40.22	12

Table 2
Ordered Set for negative cost measures applying traditional *MAC*.

Measure	MAC_m	τ_{MAC}
L	7.20	13
M	23.29	14
N	25.92	15
O	30.67	16
P	37.99	17
Q	47.07	18
R	50.85	19
S	51.51	20
T	75.75	21
U	119.87	22
V	136.73	23
W	183.93	24
X	250.98	25
Y	271.69	26

in Section 7 and finally, conclusions and limitations of the research are drawn in Section 8.

2. The traditional MAC curve and its anomalies

The traditional MAC curve offers a graphical representation of the GHG mitigation potential and the marginal costs of abatement measures in a specific period in such way that more cost-effective measures are on the left-hand side (negative values have the potential to save money) (Prada-Hernández, Vargas, Ozuna, & Ponz-Tienda, 2015). Each labelled bar represents the results of an abatement measure (m), the width of the bar represents the GHG abatement potential (ΔE_m) as the amount of equivalent CO_2 in tonnes that the measure m could potentially abate and the height represents the marginal cost of abating a tonne of CO_2 (MAC_m) in United States Dollars (USD) (Fig. 1).

MAC_m is computed by applying Eq. (1) for each abatement measure m, ΔC_m is the associated net present value (NPV) of implementing and operating it, ΔB_m is the economic benefit generated by the energy savings and ΔE_m is the abatement potential (the sum of tonnes abated during the studied time). Finally, the difference between ΔC_m and ΔB_m corresponds to the total cost of the measure, $Cost_m$.

$$MAC_m = \frac{\Delta C_m - \Delta B_m}{\Delta E_m} = \frac{Cost_m}{\Delta E_m} \tag{1}$$

The ordered set of negative cost measures for the adapted values in the case of study of Prada-Hernández, Vargas, Ozuna & Ponz-Tienda (2015) are shown in Table 1. τ_{MAC} is the ordered set of measures applying the traditional MAC method. It is important to notice that an additional measure (ZZ) was added to complement the used data. The ordered set for positive measures is shown in Table 2.

As stated previously, Taylor (2012) and Ward (2014) identified a flaw in the cost-effectiveness calculation generated by the MAC curve. This problem affects abatement measures with negative costs, in such a way that the resulting ranking favours measures that produce low emission reductions and lower monetary savings; therefore, the traditional MACC method is unreliable.

Eq. (1) shows that the measure with the smallest MAC_m presents the smallest cost per tonne of CO_2 abated (so smaller values of MAC_m are always desirable). It is also clear that the abatement potential, ΔE_m, of any measure is always positive. Thus, if a measure has a positive $Cost_m$, the marginal cost of the measure MAC_m will be positive. This case obtains a smaller MAC_m with lower $Cost_m$ or higher ΔE_m. When a measure has a negative $Cost_m$, MAC_m is smaller (more desirable) with a lower $Cost_m$ or a lower ΔE_m, which means that, opposite to what is expected, a lower CO_2 reduction is preferred (Taylor, 2012).

This can be observed in Fig. 2, where a higher ΔE_m provides a lower MAC_m when the $Cost_m$ is positive but when the $Cost_m$ is negative, as can be seen near to the zero of the ΔE_m axis, a higher abatement potential, ΔE_m, gives an undesirable higher MAC_m.

3. Alternative ranking models

3.1. The "nondominated ranking" method by Taylor (2012)

In order to rank abatement measures, Taylor (2012) proposed the application of a "nondominated ranking" method

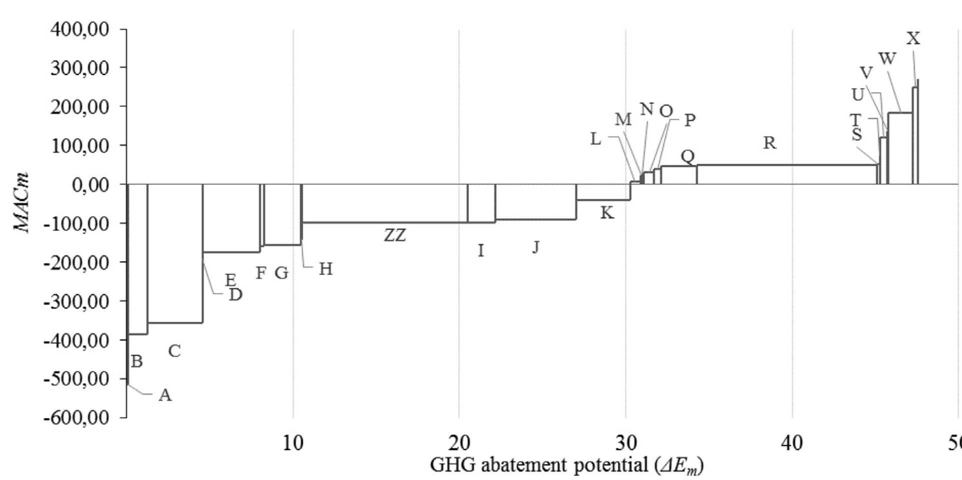


Fig. 1. Traditional MACC representation (adapted from Prada-Hernández, Vargas, Ozuna & Ponz-Tienda (2015)).

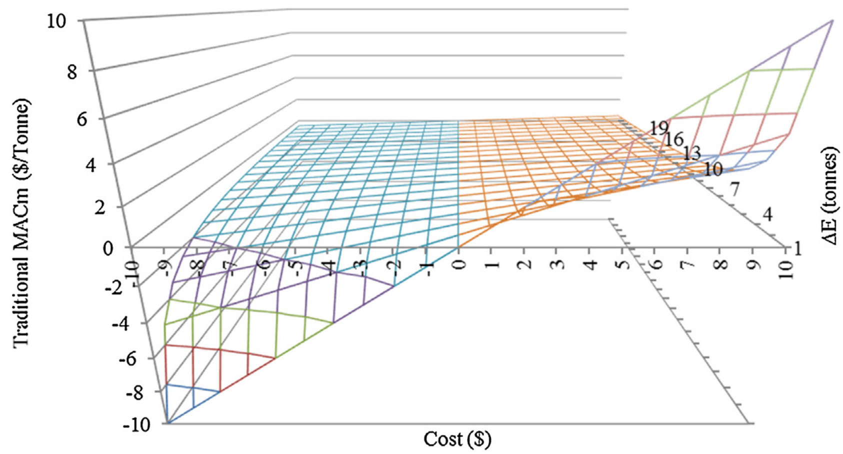


Fig. 2. MAC values for different combinations of Cost and Abatement Potential (Adapted from Taylor (2012)).

(Goldberg & Holland, 1988) by applying multi-objective optimisation and making use of the Pareto front (Deb, 2001). Taylor's method maximises two criteria: greater GHG reduction and lower costs.

The dominance concept simplifies the definition of a Pareto front, in such way that a measure A dominates a measure B if they satisfy any of these two conditions: measure A dominates measure B if the cost or abatement performance of A is better than that of B and the other is no worse (Eq. (2)).

$$\begin{aligned} &Cost_A < Cost_B \quad and \quad \Delta E_A \geq \Delta E_B \\ &\Delta E_A > \Delta E_B \quad and \quad Cost_A \leq Cost_B \end{aligned} \tag{2}$$

Fig. 3 shows the behaviour of each measure in terms of cost and the GHG abatement potential. The measure, designated by the label G, dominates all the measures represented on the upper-left quadrant defined by the red dotted lines (A, D, F, H, I) and is dominated by the lower-right quadrant (E, J, C). The measures included on the lower-left and upper-right quadrants (B K, R) do not present preference. This process is applied repeatedly for all negative cost measures in order to produce an ordered set of emissions reduction measures. All those measures with positive cost are not ranked with this approach but with the traditional MACC and cannot be compared with the negative cost measures, providing discontinuous results in two different ordered sets.

The subsets for the negative cost measures applying the Taylor method to the adapted values of the study case from Prada-Hernández, Vargas, Ozuna & Ponz-Tienda (2015) are show in Table 3. The positive values are ordered following the traditional MACC criterion (Table 2). In Table 3, the column "Subset" corresponds to the ordered group assigned by the Taylor method to each measure and τ_{Taylor} to the ordered bounds of each measure. Such "from–to" bounds mean that every measure can take any position within the range of values given, indistinctly of their individual advantages. In other words, this method does not prefer any given measure to the others in the same subset.

3.2. The Ward method (2014)

To avoid the problem of ranking abatement measures with negative cost, Ward proposed to plot a function that is directly related to the benefit, taking a range of values for avoided CO_2 and simply plotting the net benefit of each measure. The method adopts those measures for which the area under the curve (the financial benefit) added to the width of the curve (the emissions avoided) multiplied by an assumed value of avoided emission, is maximised.

According to the authorsí interpretation of the Ward method, the ordered set (τ_{Ward}) of negative cost measures for the adapted values from the case study from Prada-Hernández, Vargas, Ozuna & Ponz-Tienda (2015) is shown in Table 4 and the graphical representation of the abatement measures applying the Ward method is shown in Fig. 4. The positive values are ordered following the traditional MACC criterion (Table 2).

4. Two proposals for ranking abatement measures

We propose two novel models and a graphical representation similar to the MAC curve; the only difference is that the height of each bar represents the result of the method and not the marginal cost. Likewise, better measures are on the left-hand side.

Table 3
Ordered Subsets for negative cost measures applying Taylor method vs traditional MAC.

Measure	Subset	τ_{Taylor}	τ_{MAC}
C	1	1–4	3
E		1–4	5
J		1–4	11
ZZ		1–4	9
B	2	5–7	2
G		5–7	7
K		5–7	12
I	3	8–8	10
A	4	9–10	1
F		9–10	6
H	5	10–11	8
D	6	12–12	4

Table 4
Ordered Set for negative cost measures applying Ward method compared to traditional MAC.

Measure	$WARD_m$	τ_{Ward}	τ_{MAC}
ZZ	−9.90E+09	1	9
C	−3.92E+09	2	3
J	−2.15E+09	3	11
E	−2.06E+09	4	5
G	−7.66E+08	5	7
B	−4.86E+08	6	2
K	−4.20E+08	7	12
I	−2.66E+08	8	10
F	−9.44E+06	9	6
A	−5.02E+06	10	1
H	−6.82E+05	11	8
D	−6.88E+04	12	4

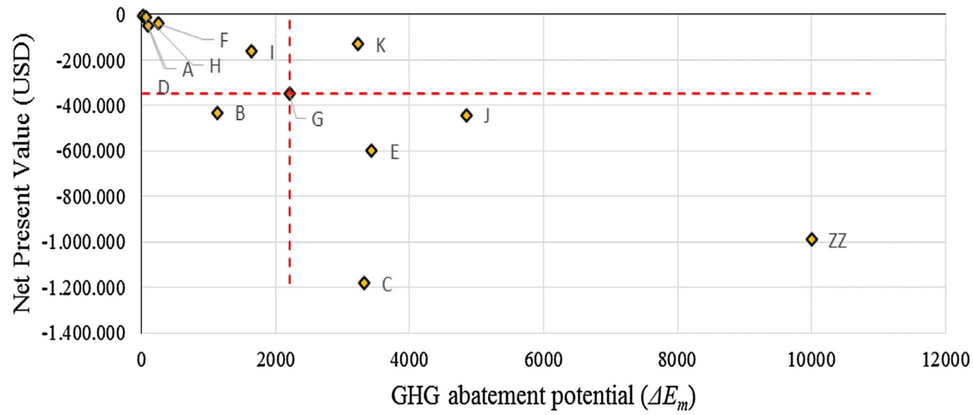


Fig. 3. Pareto front analysis for abatement negative cost measures (analysis for the G measure).

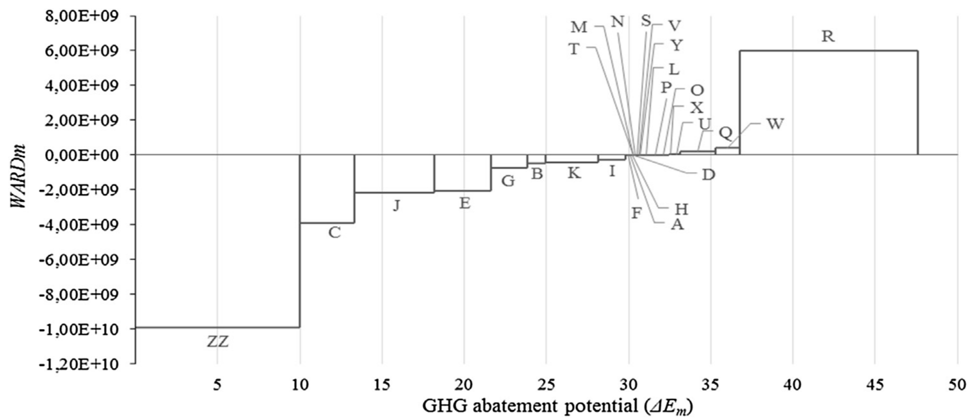


Fig. 4. Measures ordered by Ward method based on the traditional MACC representation.

4.1. The gain maximizing method

The Gain Maximizing (GM) method deals with the problem of ranking negative measures in a continuous way and favours alternatives with greater GHG reduction potential and greater Benefit/Cost (B/C) relation. This approach, unlike traditional approaches, allows comparing negative and positive cost options in a consistent way and in some cases favours greater reduction potential over low cost.

A GM_m indicator, in Eq. (3), is proposed for each abatement measure. It relates financial benefit (ΔB_m) and investment (ΔC_m) with GHG abatement potential (ΔE). In addition, to evaluate measures where $\Delta C_m = 0$, a free variable ε is added to the formula as a real number, greater than zero and lesser or equal to one. When ε is equal to one, it has no other impact than avoiding division by zero. Otherwise, the closer ε is to zero, the lower the value of GM_m and the better the measure. When the cost is equal to zero and ε is close to zero, it will favour measures with non-initial investment.

$$GM_m = \frac{-\Delta B_m}{\Delta C_m + \varepsilon} \cdot \Delta E_m \tag{3}$$

This model is always negative, so it does not differ between negative and positive measures, a case where the traditional MACC model fails.

The ordered set (τ_{GM}) for the negative and positive cost measures applying the GM method to the values from the case study from Prada-Hernández, Vargas, Ozuna & Ponz-Tienda (2015) is shown in Table 5 for $\varepsilon = 1$ and $\varepsilon = 0.001$. The corresponding graphical representation for $\varepsilon = 1$ (GM(1) henceforth) and $\varepsilon = 0.001$ (GM(ε) henceforth) can be seen in Fig. 5 and Fig. 6, respectively.

Table 5
Ordered set for negative and positive measures with the GM method compared to traditional MAC.

Measure	$\Delta C_{m,i}$	GM_m		τ_{GM}		τ_{MAC}
		$\varepsilon = 1$	$\varepsilon = 0.0001$	$\varepsilon = 1$	$\varepsilon = 0.\ 0001$	
E	0.00	−2.06E+09	−2.06E+12	1	1	5
ZZ	10,000.00	−1.00E+06	−6.82E+08	2	4	9
H	0.00	−6.82E+05	−6.88E+07	3	2	8
D	0.00	−68,789.72	−1.00E+06	4	3	4
J	405,978.24	−10,148.77	−10148.79	5	5	11
R	2,452,923.57	−8,418.89	−8,418.89	6	6	19
C	1,084,154.74	−6,935.21	−6,935.21	7	7	3
K	434,925.48	−4,194.46	−4,194.47	8	8	12
I	126,071.24	−3,759.03	−3,759.06	9	9	10
G	1,161,457.60	−2,866.29	−2,866.30	10	10	7
B	336,670.08	−2,568.75	−2,568.76	11	11	2
Q	476,269.11	−1,690.84	−1,690.84	12	12	18
F	8,099.51	−1,409.04	−1,409.21	13	13	6
W	1,271,864.74	−1,155.44	−1,155.44	14	14	24
L	96,171.53	−612.72	−612.73	15	15	13
A	10,652.24	−569.91	−569.96	16	16	1
O	126,071.24	−521.81	−521.81	17	17	16
P	322,642.95	−389.71	−389.71	18	18	17
U	336,670.08	−356.58	−356.58	19	19	22
N	25,668.83	−129.14	−129.15	20	20	15
X	121,044.22	−118.38	−118.38	21	21	25
S	25,668.83	−97.28	−97.28	22	22	20
V	86,115.56	−82.14	−82.14	23	23	23
Y	86,115.56	−61.87	−61.88	24	24	26
M	8,099.51	−33.63	−33.64	25	25	14
T	10,652.24	−13.60	−13.60	26	26	21

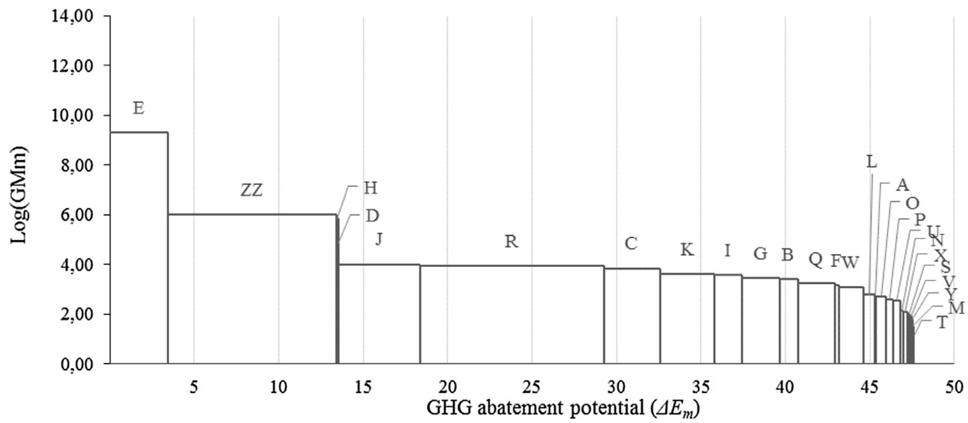


Fig. 5. Measures ordered by GM_m method (for $\varepsilon = 1$) based on the traditional MACC representation.

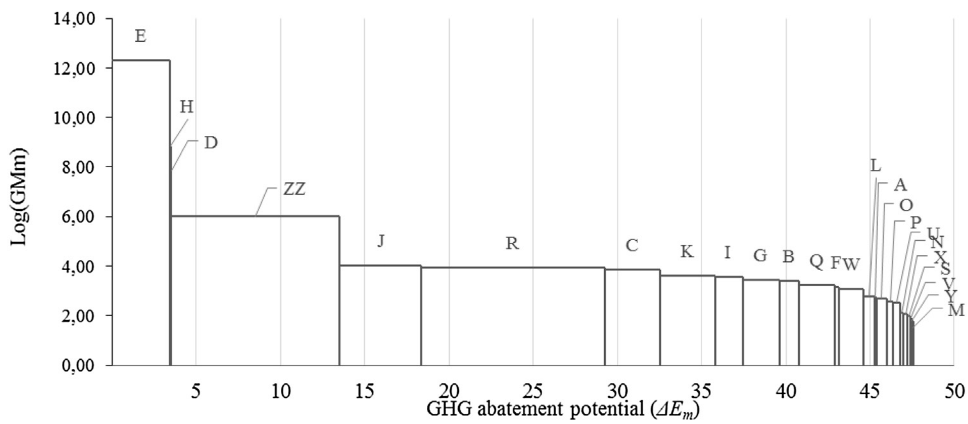


Fig. 6. Measures ordered by GM_m method (for $\varepsilon = 0.001$) based on the traditional MACC representation.

4.2. The extended MAC method

The Extended MAC (EMAC) method also allows the direct and continuous ranking of both positive and negative cost measures. In this case, the index favours those options with the lower cost and greater GHG reduction potential but also always prefers measures with negative total cost ($\Delta B_m - \Delta C_m < 0$). In other words, it prefers measures with a negative net present value to those that have an actual positive cost; consequently, it often favours low cost measures over greater reduction potential.

An $EMAC_m$ indicator is proposed in Eq. (4) for each abatement measure. Structurally, this index relates the inverse of the net present value of every measure, traditionally known as $Cost_m$ ($\Delta B_n - \Delta C_n$), with the GHG abatement potential (ΔE_m). Eq. (4) uses an exponent defined by $sign(x)$, which operates as $x/|x|$ for every value of x except zero, in which case, the exponent takes a value of zero. Therefore, for the positive cost measures, EMAC operates as the traditional MACC index, dividing $Cost_m$ by ΔE_m, and for measures with negative costs, EMAC multiplies $Cost_m$ and ΔE_m. Therefore, this method prefers measures with greater cost effectiveness in the positive range (same as traditional MACC) and prefers measures with greater abatement potential and greater cost reduction on the negative side.

$$EMAC_m = Cost_m \cdot \Delta E_m^{sign(-Cost_m)}, \; sign(x) = \begin{cases} \dfrac{x}{|x|}, & x \neq 0 \\ 0, & x = 0 \end{cases} \tag{4}$$

The ordered set (τ_{Emac}) for the negative and positive cost measures applying the EMAC method to the values from the study case of Prada-Hernández, Vargas, Ozuna & Ponz-Tienda (2015) are shown in Table 6 and the graphical representation of the abatement measures applying the EMAC method in Fig. 7.

Table 6
Ordered set for negative and positive measures with the EMAC Method compared to traditional MAC.

Measure	$Emac_m$	τ_{Emac}	τ_{MAC}
ZZ	−9.90E+09	1	9
C	−3.92E+09	2	3
J	−2.15E+09	3	11
E	−2.06E+09	4	5
G	−7.66E+08	5	7
B	−4.86E+08	6	2
K	−4.20E+08	7	12
I	−2.66E+08	8	10
F	−9.44E+06	9	6
A	−5.02E+06	10	1
H	−6.82E+05	11	8
D	−6.88E+04	12	4
L	7.20	13	13
M	23.29	14	14
N	25.92	15	15
O	30.67	16	16
P	37.99	17	17
Q	47.07	18	18
R	50.85	19	19
S	51.51	20	20
T	75.75	21	21
U	119.87	22	22
V	136.73	23	23
W	183.93	24	24
X	250.98	25	25
Y	271.69	26	26

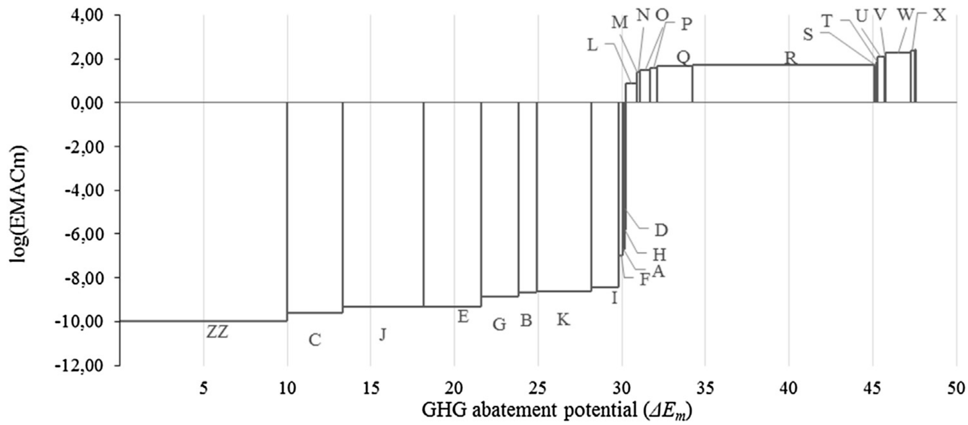


Fig. 7. Measures ordered by EMAC method based on the traditional MACC representation.

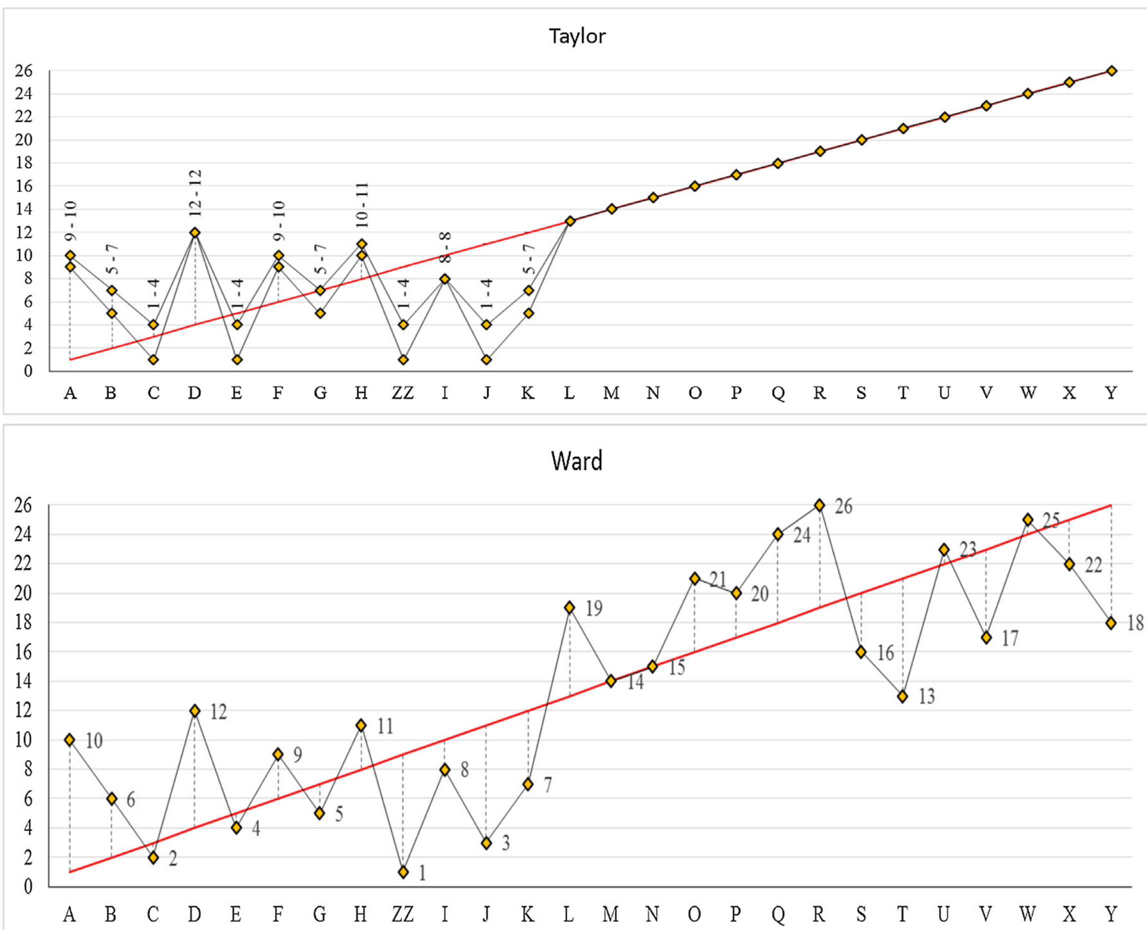


Fig. 8. Comparison of Taylor and Ward methods with Traditional MAC method (red line) (for interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

5. Comparison and discussion of MAC, EMAC and GM methods

The previously detailed methods deal with the problem of ranking GHG abatement measures with positive and negative costs under different approaches by providing different ordered sets. These differences are summarised Fig. 8 and Fig. 9. The x-axis represents the abatement measures and the y-axis the order assigned by each method. The differences of the Taylor and Ward methods versus the traditional MACC (red line) are represented in Fig. 8 and the differences of the proposed methods, GM and EMAC with different values of ε, in Fig. 9. In the upper side of Fig. 8 (Taylor method) the two values represent the bounds of the subset produced by the Taylor method.

Along the previous sections, we have not discussed the problem of selecting the best method. There is no correct answer to this question, it depends on what attributes are preferred. Some methods can choose measures with high environmental impacts and others favour measures with high economical profit. Therefore, we will propose a categorisation of the methods under the

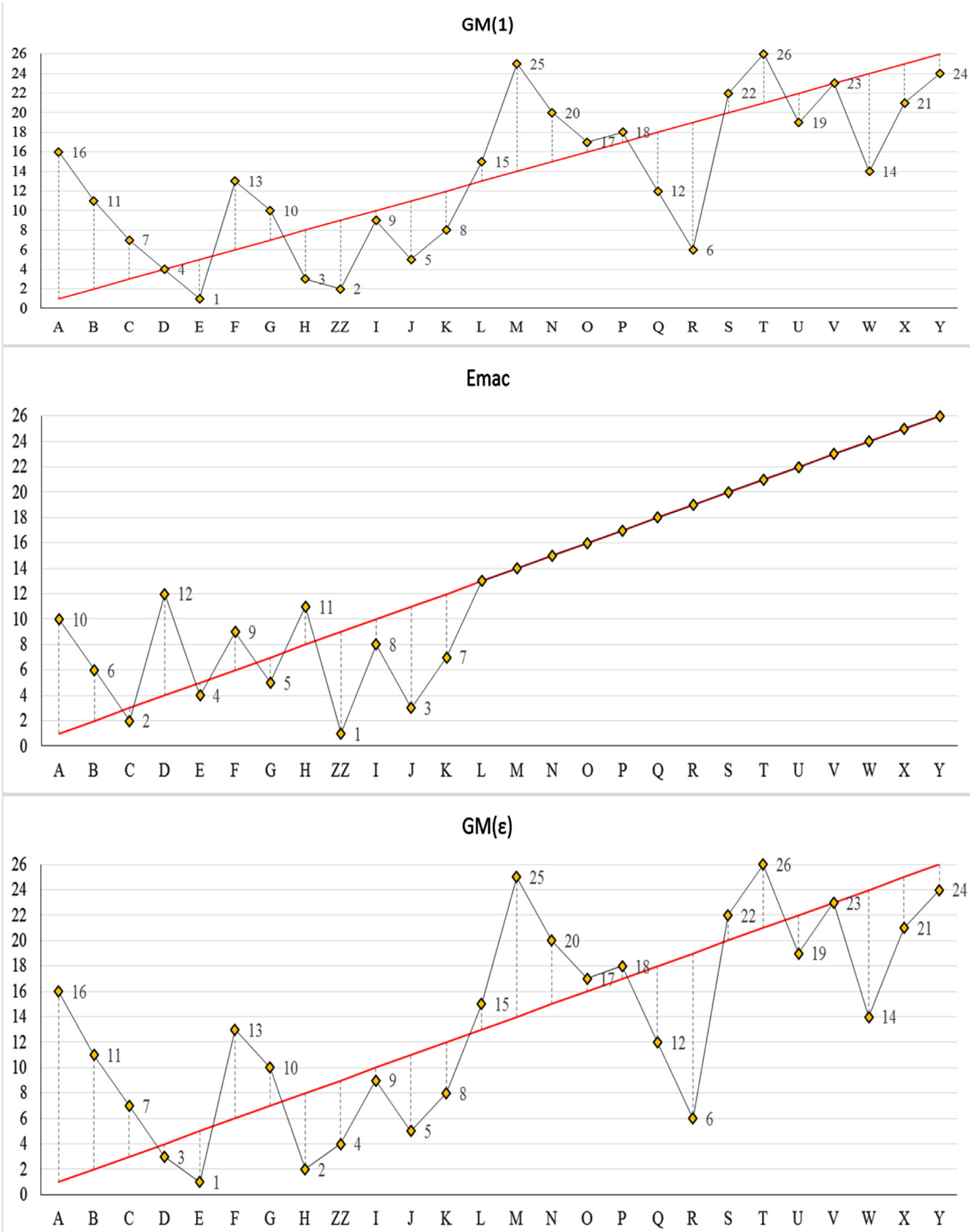


Fig. 9. Comparison of Gain Maximizing with two epsilon values (GM(1), GM(ε)) and extended MAC (EMAC) with Traditional MACC method (red line) (for interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

attributes of an "environmentalist" method and an economical "greedy" method. This will allow us to establish a framework to develop a Balanced Ordering Method (BOM) that gathers the goodness of the approaches, enabling decision makers to represent their specific interests in the ranking of GHG abatement measures.

Clearly, it is not possible to compare the previously described methods in a direct way since the magnitudes differ widely. Therefore, the ranking that every method induces over a set of projects will be used for the analysis. For this purpose, it is necessary to introduce some notation:

- A seed method μ is a function $\mu : \mathbb{R}^3 \to \mathbb{R}$
- A measure $m_i = (\Delta C, \Delta B, \Delta E)$ is a point on $\mathbb{R}^3$
- Given a set M with n measures, τ_μ is a function $\tau_\mu : M \to [1 \cdots n]$ such that:

$$\tau_\mu(m_1) \leq \tau_\mu(m_2) \leftrightarrow \mu(m_1) \leq \mu(m_2) \tag{5}$$

So $\tau_{\mu}(m_1)$ ranks the measure m_i, according to the results of the method μ.

To decide how “environmentalist” or “greedy” each method is, two referential benchmarks are introduced in Eqs. (6) and (7), the environmentalist (ENV) and the greedy (GRE), respectively:

$$ENV(\Delta C, \Delta B, \Delta E) = -\Delta E \tag{6}$$

$$GRE(\Delta C, \Delta B, \Delta E) = \Delta C - \Delta B \tag{7}$$

On one hand, the ENV rank orders measures focusing only on GHG abatement potential; hence, it is the most “environmentalist”. On the other hand, the GRE rank, orders the measures solely based on cost, therefore it is the “greediest” order. To measure how close the rank is given by a certain method to the ENV and GRE orderings, the Kendall tau distance $K(\tau_{\mu 1}, \tau_{\mu 2})$ (Kendall, 1948) for two method $\mu 1$ and $\mu 2$, is used and given by Eq. (8). Given two orders for a finite set M, Kendall tau's distance measures the similarity between such orders and computes each unique pair of elements of M (there are $\binom{\#M}{2}$ unique pairs in M) and then compares how the methods order each pair and count the number of inconsistences between the two orders.

$$\begin{aligned} K(\tau_{\mu 1}, \tau_{\mu 2}) &= \frac{\left\{\#\left(m_i, m_j\right) \in M^2 : i > j, \left(\tau_{\mu 1}(m_i) - \tau_{\mu 1}\left(m_j\right)\right) \cdot \left(\tau_{\mu 2}(m_i) - \tau_{\mu 2}\left(m_j\right)\right) < 0\right\}}{\binom{n}{2}} \\ &= \frac{\left\{\#\left(m_i, m_j\right) \in M^2 : i > j, \mu 1, \mu 2 \text{ are inconsistent with respect to } \left\{m_i, m_j\right\}\right\}}{\binom{n}{2}} \end{aligned} \tag{8}$$

The Kendall tau distance, $K(t_{\mu 1}, t_{\mu 2})$, indicates the percentage of unique pairs of measures [i, j] (which is represented by the expression $i < j$ in Eq. (8)) whose ranking differs with respect to $t_{\mu 1}$ and $t_{\mu 2}$ rankings. For $\mu 1$and$\mu 2$ methods and $m_1, m_2 \in M$ measures: $\mu 1$and$\mu 2\mu 1$and$\mu 2$ are inconsistent with respect to $\{m_1, m_2\}$ if the order given by $\mu 1$ over $\{m_1, m_2\}$(considering these two elements only) differ from the given by$\mu 2$. For example if the rank given by $\mu 1$ for m_1 is higher than for m_2 but the opposite occurs for $\mu 2$ (i.e., the rank given by $\mu 2$ for $m_1$is lower than for m_2) then $\mu 1$ and $\mu 2$ are inconsistent with respect to $\{m_1, m_2\}$. In other words, the Kendall tauís distance counts the number of inconsistences for two given methods with respect to all distinct pairs in M. All possible outcomes are shown in Table 7.

Therefore, the closer K is to zero, the greater the similarities between $t_{\mu 1}$ and $t_{\mu 2}$. Fig. 10 shows the Kendall tau distance to the greediest (GRE) and more environmentalist (ENV) benchmarks for the analysed methods using the data from Prada-Hernández, Vargas, Ozuna & Ponz-Tienda (2015).

From Fig. 10 is easy to appreciate that methods MACC, Ward, EMAC and Taylor are greedy methods ($K(t_{\mu}, t_{GRE})$ closer to zero), while methods GM(1) and GM(ε) are environmentally friendly methods ($K(t_{\mu}, t_{ENV})$ closer to zero). Therefore, the selection of the ranking method depends on the specific interests of the decision maker (DM) in terms of the importance between the potential GHG reduction and the economical profit.

It is possible that none of the above methods meet the particular needs of the decision maker. In order to address this issue, we present a balancing methodology to create alternative ranking criteria based on a combination of the previously analysed methods.

6. The Balanced Ordering Method (BOM)

If μ_1 and μ_2 are seed methods and M is a set of measures, the Balanced Ordering Method ($BOM^{\alpha}(\mu_1, \mu_2)$) is a function (Eq. (9)), in such that given the ordered sets of measures ($\tau_{\mu_1}$and τ_{μ_2}) $BOM^{\alpha}(\mu_1, \mu_2)$ can build a new balanced method $\xi^{\alpha} = BOM^{\alpha}(\mu_1, \mu_2)$, where τ_{ξ} is the balanced ranking of the seed ordered sets τ_{μ_1} and τ_{μ_2} for a given α (Eq. (10)). In other words, $BOM^{\alpha}(\mu_1, \mu_2)$ weights the rankings τ_{μ_1}andτ_{μ_2}.

$$BOM^{\alpha}(\mu_1, \mu_2) : \mathbb{R}^3 \to \mathbb{R} \tag{9}$$

$$BOM^{\alpha}(\mu_1, \mu_2)(m) = \alpha \cdot \tau_{\mu_1}(m) + (1-\alpha) \cdot \tau_{\mu 2}(m), \alpha \in [1, 0] \tag{10}$$

For a better comprehension of Eqs. (9) and (10), we implement this methodology for the data from Prada-Hernández, Vargas, Ozuna & Ponz-Tienda (2015) and the ranking methods EMAC and GM(1). We assume that $\tau_{Emac} = \tau_{\mu_1}$ and $\tau_{GM(1)} = \tau_{\mu_2}$. Applying Eq. (10) results in:

$$\xi^{\alpha} = BOM^{\alpha}(EMAC, GM(1)) = \alpha \cdot \tau_{Emac} + (1-\alpha) \cdot \tau_{GM(1)} \tag{11}$$

Fig. 11 shows the comparison of results in computing ξ between *EMAC* and *GM(1)* for $\alpha \in \{0, 0.25, 0.5, 0.75, 1\}$. Note that the result of ξ^{α} is τ_{Emac} when $\alpha = 1$, and $\tau_{GM(1)}$ when $\alpha = 0$.

Fig. 12 shows the Kendall tau distance to the GRE and ENV benchmarks for the five ordered sets presented in Fig. 11. It can be observed that lower values of α produce results closer to the seed ranking method (GM(1)) and closer to the ENV benchmark. Similarly, values of α closer to one produce rankings closer to the first seed method (EMAC) and consequently more greedy rankings.

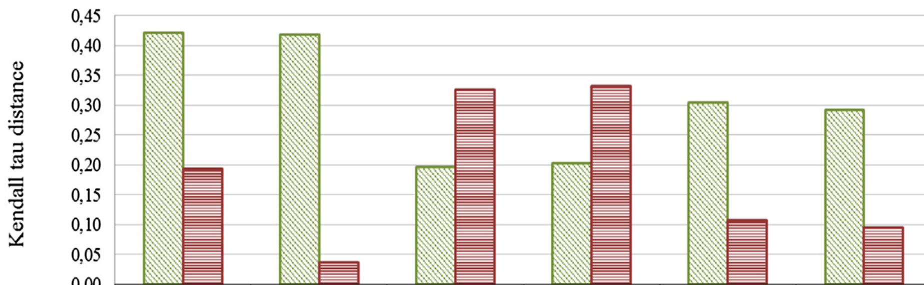
7. United nations for Colombia development case study

To show the differences of the proposed methodology in comparison with related approaches found in the literature, we analysed the ranking proposed by Behrenz E. (2014) for the United Nations programme for the development of Colombia. They analysed a set of mitigation measures in the context of Colombia in terms of cost-effectiveness by applying the MACC methodology for the principal emitting sectors.

For the purpose of this comparison, the results obtained for the industrial sector were selected because it contains many negative cost mitigation measures, providing an illustrative scenario where MAC curves do not produce coherent results. Comparison of the

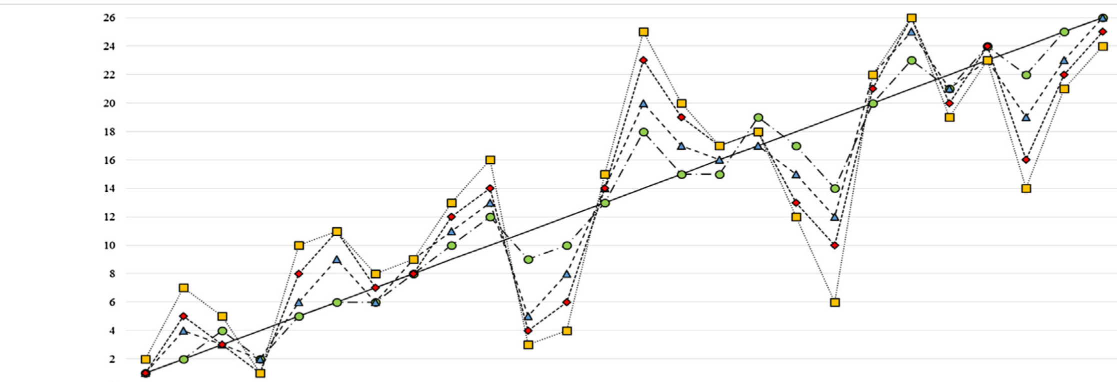
Table 7
All possible consistency outcomes for the Kendall tau distance.

Order respect to $\mu 1$	Order respect to $\mu 2$	Consistency	$\left(\tau_{\mu 1}(m_1) - \tau_{\mu 1}(m_2)\right) \cdot \left(\tau_{\mu 2}(m_1) - \tau_{\mu 2}(m_2)\right)$
$\tau_{\mu 1}(m_1) \geq \tau_{\mu 1}(m_2)$	$\tau_{\mu 2}(m_1) \geq \tau_{\mu 2}(m_2)$	Consistent Order	≥ 0
$\tau_{\mu 1}(m_1) \geq \tau_{\mu 1}(m_2)$	$\tau_{\mu 2}(m_1) < \tau_{\mu 2}(m_2)$	Inconsistent Order	< 0
$\tau_{\mu 1}(m_1) < \tau_{\mu 1}(m_2)$	$\tau_{\mu 2}(m_1) \geq \tau_{\mu 2}(m_2)$	Inconsistent Order	< 0
$\tau_{\mu 1}(m_1) < \tau_{\mu 1}(m_2)$	$\tau_{\mu 2}(m_1) < \tau_{\mu 2}(m_2)$	Consistent Order	≥ 0



	MAC	Ward	GM(1)	GM(e)	Emac	Taylor
Environmentalist K(τ(μ),τ(ENV))	0,42	0,42	0,20	0,20	0,30	0,29
Greedy K(τ(μ),τ(GRE))	0,19	0,04	0,33	0,33	0,11	0,10

Fig. 10. Comparison of Kendall tau distance for the analysed methods against the greediest (GRE) and environmentalist (ENV) benchmarks.



	ZZ	C	J	E	G	B	K	I	F	A	H	D	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y
EMAC=τξ(1)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
τξ(0.75)	1	2	4	2	5	6	6	8	10	12	9	10	13	18	15	15	19	17	14	20	23	21	24	22	25	26
τξ(0.50)	1	4	3	2	6	9	6	9	11	13	5	8	14	20	17	16	17	15	12	22	25	21	23	19	23	26
τξ(0.25)	1	5	3	1	8	11	7	8	12	14	4	6	14	23	19	17	18	13	10	21	26	20	24	16	22	25
GM(1)=τξ(0)	2	7	5	1	10	11	8	9	13	16	3	4	15	25	20	17	18	12	6	22	26	19	23	14	21	24

Fig. 11. BOM method applied to EMAC and GM(1) for different alpha values from one to zero.

	EMAC = BOM(EMAC, GM1), α=1	BOM(EMAC, GM1), α=0.75	BOM(EMAC, GM1), α=0.5	BOM(EMAC, GM1), α=0.25	GM1 = BOM(EMAC, GM1), α=0
Environmentalist K(τ(μ),τ(ENV))	0,30	0,27	0,24	0,22	0,20
Greedy K(τ(μ),τ(GRE))	0,11	0,15	0,22	0,27	0,33

Fig. 12. Comparison of Kendal tau distance for the BOM method applied to EMAC and GM ($BOM^{\alpha}(EMAC, GM(1))$) for different alpha values.

ranking produced by the MAC curve against the proposed methodology is presented in Table 8. Following the proposed methodology, the Kendall-Tau distance of the ordered sets exposed in Table 8 is compared to the ENV and GRE benchmarks (Fig. 13).

The dashed red line in Fig. 13 represents the boundary established by $BOM^{\alpha}(GRE, ENV)$ by all the possible measures that can be produced varying alpha between zero (ENV) to one (GRE). All the values observed above the dashed red line, as traditional MAC, are far away from the ideal measures (zero distance to GRE and ENV). This implies that the ranking produced by MACC, which is the vertical projection over the dashed red line (vertical black arrow), could be replaced and improved by an alternative rank produced by BOM for some value of alpha.

For the Behrentz (2014) study, the EMAC ranking presents a more greedy (0.05 vs. 0.31) and environmentalist (0.37 vs. 0.69) approach than the traditional MAC. This is produced because the study includes many negative cost measures and, in this case, MACC prioritises measures with low abatement potential and high nega-

Table 8
The compared values of the proposed methodology against the MAC order by Behrentz (2014).

Industry	τ_{MAC}	τ_{Emac}	τ_{GRE}	τ_{ENV}
Energy use of solid-waste – transversal	20	20	22	1
Recycling – transversal	21	22	23	2
Direct reduction of iron ore with Hylsa technology	9	1	1	3
Replacing coal with biomass – cement	17	3	3	4
Reducing the proportion of clinker – cement	18	4	9	5
CO2 capture and geological storage – cement	24	24	24	6
Improved efficiency of bagasse boilers – food and drinks	19	19	19	7
Production change wet to dry process – cement	21	21	21	8
Improving efficiency of oil-fired boilers – paper	5	2	2	9
Improving efficiency of coal and diesel boilers – paper	14	5	4	10
Improving efficiency of natural gas boilers – paper	10	6	4	11
Improving efficiency of natural gas boilers – chemicals	10	9	8	12
Improving efficiency of natural gas boilers – food and drinks	10	7	6	12
Improving efficiency of LPG boilers – food and drinks	7	7	6	12
Hydrogen recovery in ammonia production	23	23	20	15
Improving efficiency of diesel-oil boiler – food and drinks	1	10	10	16
Replacing coal with biomass – food and drinks	16	12	14	16
Improving efficiency of oil-fired boilers – food and drinks	5	11	12	18
Replacing coal with biomass – chemicals	13	15	15	19
Improving efficiency of fuel-oil boiler – paper	2	14	13	20
Replacing coal with biomass – paper	14	16	17	20
Improving efficiency of LPG boilers – chemicals	7	13	11	22
Improving efficiency of diesel-oil boiler – chemicals	3	17	16	23
Improving efficiency of fuel-oil boiler – food and drinks	4	18	17	24

Table 9
Kendal tau distance between the analysed measures for the Behrenz (2014) industry sector study.

	GRE	*ENV*
MAC	0.31	0.69
Emac	0.05	0.37
GRE	0.00	0.42
ENV	0.42	0.00
BOM	0.22	0.18

tive costs, thus producing rankings without a clear policy direction. The BOM ordered set is computed with EMAC and ENV as seed measures using alpha = 0.5 because we want to balance the distance from EMAC to ENV. The $BOM^{\alpha=0.5}(Emac, ENV)$ ranking offers a balanced ranking between the benchmark methods slightly under the boundary, implying that is better than any BOM combination of ENV and GRE (Table 9).

8. Conclusions

The ranking of GHG abatement measures are important for decision makers to identity instruments and policies that justify investment decisions. Traditionally, MAC curves re considered a standard tool for analysing the impacts of mitigation measures promoted by governments and one of the most used methodologies for evaluating which abatement options to implement by comparing their cost-effectiveness. However, in the last years some discrepancies have arisen relating to its construction and interpretation.

We analysed the methods found in the literature for evaluating and ranking abatement measures, identified unsolved issues and proposed three alternative novel methods that produce continuous rankings for positive and negative costs, allowing an objective and consistent analysis of different alternatives.

The first method, GM, supports an environmentalist attitude and performs a direct comparison of measures with negative and positive costs. The second, the EMAC method, considers the economically driven point of view of the decision maker, weighting the negative cost options according to its economic savings over its reduction potential. The third is a BOM, consisting of a linear-weighted combination of two discretional seed methods, which allows decision makers to take into account their goodness in order to create new rankings adjustable to a specific GHG policy, whether

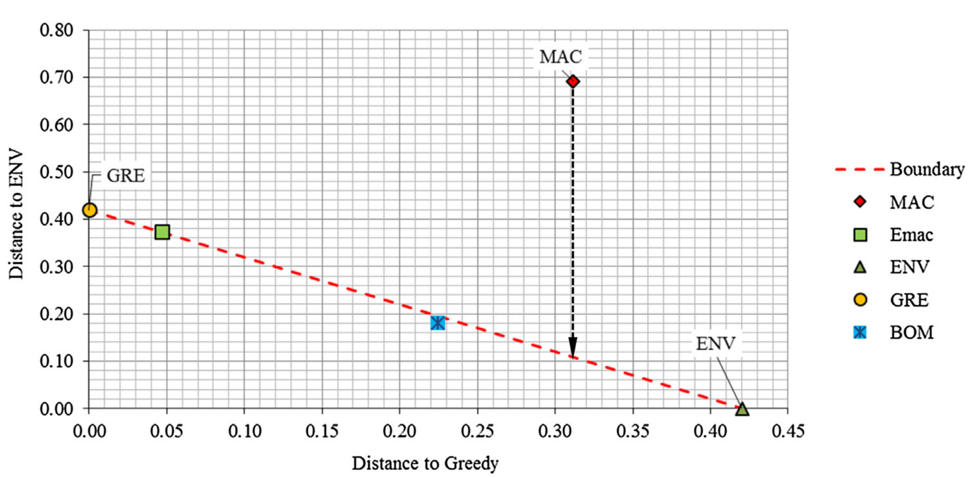


Fig. 13. Kendall tau distance between the ordered sets exposed in Table 8 compared to the ENV and GRE benchmarks.

it is fully or partially driven by economical or environmental positions.

However, it is not possible to establish which methods may be better than others; moreover, each method is suitable for different situations or positions of the decision maker. Therefore, based on the need for an objective comparison between methods we proposed a methodology for comparing methods based on their Kendal tau distance to certain benchmarks considered relevant in the decision making process (economical profit and environmental benefit).

The present research does not consider the intersectoral, intertemporal and macroeconomic interactions or the wider social implications related to climate change mitigation. Future research should aim to define an alternative method in order to consider these shortcomings.

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