Marginal abatement Cost Curves (MACC): unsolved issues, and alternative proposals

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Abstract

Policy makers and economists proposed the MACC as an instrument to rank possible Greenhouse gases (GHG) mitigation measures available in a market. This tool orders measures according to their cost-efficiency, taking into account only two variables: costs and emissions reductions. Although MACC has been used in relevant settings like the first treaty of the United Nations Framework Convention on Climate Change (UNFCCC), it has shown mathematical failures that might produce unreliable rankings. This chapter presents existing alternatives to the use of traditional MAC curves for ranking GHG abatement measures: (1) Taylor's method that is based on the application of the dominance concept. (2) Ward's method that is directly related to the net benefit of each measure. (3) The GM method, which supports an environmentalist attitude and performs a more reliable comparison of measures with negative and positive costs. (4) The EMAC method corresponds to an extension of the traditional MACC and considers the economically driven point of view of the decision maker. (5) And the BOM method, consisting of a linear-weighted combination of two discretional seed methods, allowing decision makers to take into account the goodness of multiple methods. This last one creates new rankings that are adjustable to a specific GHG policy, whether it is fully or partially driven by economical or environmental positions. Finally, several case studies and discussions are presented, showing the advantages of the exposed methods.

Keywords.

1. *Introduction*

Policy makers around the world are substantially committed to the reduction of carbon emissions, energy efficiency and fuel substitution (Balsalobre Lorente, Álavrez-Herránz, & Baños Torres, 2016) (Cantos & Balsalobre Lorente, 2011; 2013), because the global energy use and its corresponding emissions will grow.

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However, they face several difficulties in finding appropriate solutions to greenhouse gas (GHG) mitigation without imposing heavy economic burdens on society, in a context of limited budgets and divergent interests.

Policy makers use 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 D. , y otros, 2008) (Prada-Hernández, Vargas, Ozuna, & Ponz-Tienda, 2015) (Bockel, Sutter, Touchemoulin, & Jönsson, 2012) (Moran D. , y otros, 2010). These help them to identify policies and appropriate instruments to justify investment decisions (Kesicki F. , 2013) and to demonstrate how much abatement an economy can afford and the focus area to achieve targeted emission reductions (Vogt-Schilb & Hallegatte, 2014).

In the challenge of designing decarbonizing policies in an economically efficient manner, policy makers rank and prioritise available abatement measures to minimize costs and maximize mitigation potentials through MAC curves. These show the economic feasibility of climate change mitigation, representing the marginal cost of emission abatement for varied technologic options (Kesicki & Ekins, 2012) Some authors have recognized that MACC have methodological failures. Which are mainly presented for negative-cost measures (Kesicki F. , 2012). Due to its relevance, we present and evaluate the methods for raking abatement measures.

In Section 2 we describe the fundamentals of the MACC method and its failures. Sections 4 to 8 briefly present the alternative ranking methods for negative cost measures available in the literature. In the Section 9, it is exposed a classification method based on the distance between environmental and economic "referential benchmarks". Several case studies and discussions are presented in Section 10. Finally, conclusions and limitations of the research are drawn.

2. *The traditional MAC method and its failures*

MAC curves were developed by Paulson (1948), transformed by Jackson (1991) to fit a climate change context, as a graphical representation of ordered energy measures that relates the potential of mitigation against its marginal costs, in such way that more cost-effective measures are on the left-hand side. The measures (m) are represented as labelled bar, in which the width represents the GHG[5] abatement potential (ΔE_m) and the height represents the marginal cost of abating a tonne of CO_2 (MAC_m). For computing the MAC_m for each measure (m), equation (1) is by applied using the following criteria: 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, ΔE_m is the abatement potential (the sum of tonnes abated during the studied time), and $Cost_m$ is the total cost of the measure, as the difference between ΔC_m and ΔB_m.

[5] Expressed as equivalent CO_2 in tonnes that a measure m could potentially abate.

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

The use of MAC curves is generalized, being considered a standard and extremely efficient tool for analysing and communicate the results regarding the economic implications and impacts of energy policies for climate mitigation. Nevertheless, some discrepancies arose relating to the calculation, construction and interpretation of MAC curves in recent years.

The first warnings about MAC curves was stated by Kesicki & Strachan (2011) and Kesicki & Ekins (2012), stating that its simplistic approach possibly biases the decision-making, not taking into account the intersectoral, intertemporal and macroeconomic interactions, as well as the social implications related to climate change mitigation.

Nevertheless, the most controversial issue is the cost-effectiveness calculation that generates the MAC curves relating to win-to-win measures with negative costs (negative net present value). The problem is that MAC curves use the same criteria for ranking abatement measures with positive and negative costs, that favours measures with low emission reductions over options with the same negative cost but greater CO_2 reduction potential, and consequently producing unreliable rankings (Levihn, 2016) (Huang, Kuo, & Chou, 2016).

If a measure has a positive $Cost_m$, the marginal cost of the measure MAC_m will be positive, and smaller values of MAC_m are always desirable, but 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. In Figure 1 is shown the schematic MAC curve for 5 measures used by Ward (2014), each with the same financial benefit ($ 250) but saving different amounts of CO_2 (1, 2, 3, 4 and five respectively). This example allows us to see the potential error of the conventional interpretation of MAC curves, because the measure with the largest negative specific marginal cost, measure 5, is preferred (MAC_5 = -250; Tons CO_2=1). Since they all have the same financial benefit, the measure with the largest emissions reduction, measure 1 (MAC_1 = -50; Tons CO_2=5), should be the preferred one.

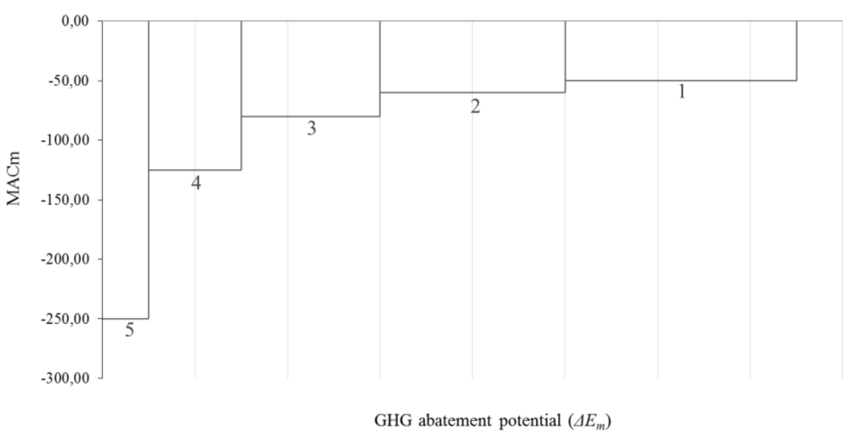

Figure 1 Schematic MAC curve for five measures from Ward (2014)

The problem of ranking options with negative marginal cost was already identified by Wallis (1992a; 1992b), but without a rigorous discussion by the scientific community of its methodological implications for about 20 years. Ackerman & Bueno (2011) avoided this issue by assuming a near-zero positive cost instead of negative-cost, stating that negative costs are controversial among economists and problematic for modelling purposes. Kesicki & Ekins (2012) disputed the existence of negative abatement costs, arguing these costs are not compatible with an efficient market.

Taylor (2012), Ward (2014) and Ponz-Tienda et al (2016) do not take into account the previously exposed arguments but instead focused on the mathematical treatment and accuracy of the ranking of options that negative cost.

Recently, Levihn (2016) states that some approaches as Pareto optimization (Taylor, 2012) to solve the problem of ranking GHG abatement measures would result in undesirable effects. Finally, the same author says that using economic efficiency (least cost per unit supplied) as a metric would "*fulfil the requirements of least cost integrated planning when options result in a negative marginal cost*" and that "*another metric would be needed, but would not per-se result in least cost planning*".

3. *The Taylor's method for ranking negative abatement measures*

Taylor (2012) was the first author to propose a mathematical solution for this issue maximizing two criteria: greater GHG reduction and lower costs by the application of the dominance concept (Goldberg & Holland, 1988). The dominance concept simplifies the definition of a Pareto front (Deb, 2001), in such way that a measure A dominates a measure B (quadrant 4) if the cost or abatement performance of A is better than that of B and is no worse (equation (2)). Additionally, it neither dominates nor is dominated by the grey points in quadrants 2 and 3 (Figure 2).

$$\begin{array}{ccc} Cost_A < Cost_B & and & \Delta E_A \geq \Delta E_B \\ \Delta E_A > \Delta E_B & and & Cost_A \leq Cost_B \end{array} \qquad (2)$$

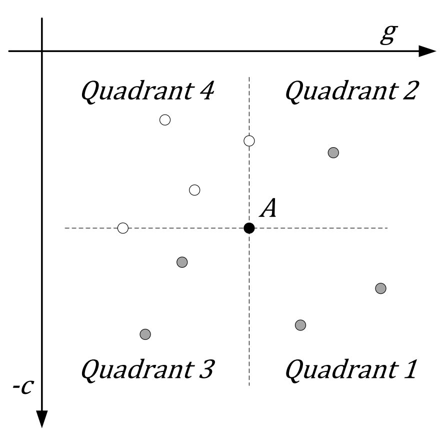

Figure 2 Definition of a Pareto front for emissions reduction measures (Taylor, 2012).

4. The Ward method

To avoid the problem of ranking abatement measures with negative cost, Ward (2014) 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.

Ward (2014) recommended plotting a function more directly related to the benefit (negative costs) and correctly set priorities for negative and positive cost independently: "*In terms of policy implications it is recommended that even though MAC curves have a role to play in ranking efficiency measures with net positive costs, they should never include measures which have net financial benefit as the interpretation of these curves is complex and counter-intuitive, completely negating the value of this simple tool for policy decisions*".

5. The Gain Maximizing (GM) method

The Gain Maximizing (GM) method is proposed by Ponz-Tienda et al (2016) to deal 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 (equation (3)), is calculated for each abatement measure. It relates the 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. This model is always negative, so it does not differ between negative and positive measures, a case where the traditional MACC model fails.

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

6. The Extended MAC (EMAC) Method

The Extended MAC (EMAC) method, proposed by by Ponz-Tienda et al (2016), also allows the direct and continuous ranking of both positive and negative cost measures, favouring those options with the lower cost and greater GHG reduction potential and giving priority to measures with negative total cost ($\Delta B_m - \Delta C_m < 0$) over greater reduction potential. The $EMAC_m$ indicator exposed in equation (4) relates the inverse of the net present value of every measure ($Cost_m = \Delta B_n - \Delta C_n$), with the GHG abatement potential (ΔE_m).

For positive cost measures, EMAC operates as the traditional MACC index, and for measures with negative costs, EMAC 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.

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

7. The environmentalist (ENV) and the greedy (GRE) methods

The previously exposed methods rank abatement measures providing different ordered sets, some favouring measures with high environmental impacts, others favouring measures with high economical profit. These two new ranking methods (Ponz-Tienda, Prada-Hernández, & Salcedo-Bernal, 2016) are "referential benchmarks" to establish the limit bounds under "environmentalist" or economical "greedy" attributes. In this way, the environmentalist (ENV) method ranks the abatement measures considering only the GHG abatement potential (eq. 5), hence, it is the "environmentalist" ranking bound. On the other hand, the greedy (GRE) method (eq. 6) orders the measures solely based on total cost of the measure ($Cost_m$), as the difference between ΔC_m and ΔB_m, hence, it is the "greedy" ranking bound.

$$ENV_m = -\Delta E_m \tag{5}$$

$$GRE_m = Cost_m = \Delta C_m - \Delta B_m \tag{6}$$

8. The Balanced Ordering (BOM) Method

It is possible that none of the above methods meet the particular needs of the decision maker. In order to address this issue, Ponz-Tienda et al (2016) proposes the Balanced Ordering Method (BOM) to create alternative ranking criteria based on a combination of the previously analysed methods, gathering the goodness of present and future approaches, enabling decision makers to rank of GHG abatement measures under their specific interests, answering how "environmentalist" or "greedy" each method is.

To compare the previously exposed methods in a direct way, it is necessary to introduce some notation:

- A seed method μ is a function $\mu: \mathbb{R}^3 \rightarrow \mathbb{R}$
- 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 $\tau_\mu: M \rightarrow [1 \cdots n]$ such that:

$$\tau_\mu(m_1) \leq \tau_\mu(m_2) \leftrightarrow \mu(m_1) \leq \mu(m_2) \tag{7}$$

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

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 (equation (8)), 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 (equation (9)). In other words, $BOM^{\alpha}(\mu_1,\mu_2)$ weights the rankings $\tau_{\mu_1}$and τ_{μ_2}.

$$BOM^{\alpha}(\mu_1,\mu_2): \mathbb{R}^3 \rightarrow \mathbb{R} \tag{8}$$

$$BOM^{\alpha}(\mu_1,\mu_2)(m) = \alpha \cdot \tau_{\mu_1}(m) + (1-\alpha) \cdot \tau_{\mu 2}(m), \alpha \in [1,0] \tag{9}$$

The α coefficient balances the obtained set, in such way that a for α=1 the set obtained is τ_{μ_1}, for $\alpha = 0 \rightarrow \tau_{\mu 2}$, and varying α between 0 and 1 an adjusted set according to the specific interests of the decision makers.

9. The classification of ranking methods (tau distance to ENV and GRE)

To measure how "environmentalist" or economical "greedy" is an ordered set of abatement measures, Ponz-Tienda et al (2016) proposes the use of the Kendall tau distance $K(\tau_{\mu 1},\tau_{\mu 2})$ (Kendall, 1948), in such way that the closer K is to zero, the greater the similarities between $t_{\mu 1}$ and $t_{\mu 2}$.

Given two orders for a finite set M, Kendall tau's distance measures the similarity between such orders ($\mu 1$ and $\mu 2$) by comparing how the methods order each pair and counting the number of inconsistences between the two orders (equation (10)).

$$\begin{aligned} K(\tau_{\mu 1},\tau_{\mu 2}) &= \frac{\left\{\#(m_i,m_j) \in M^2 : i > j, \left(\tau_{\mu 1}(m_i) - \tau_{\mu 1}(m_j)\right) \cdot \left(\tau_{\mu 2}(m_i) - \tau_{\mu 2}(m_j)\right) < 0\right\}}{\binom{n}{2}} \\ &= \frac{\left\{\#(m_i,m_j) \in M^2 : i > j,\ \mu 1, \mu 2 \textit{ are inconsistent with respect to } \{m_i,m_j\}\right\}}{\binom{n}{2}} \end{aligned} \tag{10}$$

The Kendall tau method, indicates the percentage of unique pairs of measures $[i,j]$ 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 $\mu 2$ are inconsistent with respect to $\{m_1, m_2\}$ if the order given by $\mu 1$ over $\{m_1, m_2\}$ differ from the given by $\mu 2$. In other words, the Kendall tau´s distance method counts the number of inconsistences for two given methods with respect to all distinct pairs in M.

Comparing the results of different ordering methods for several abatement measures against the referential benchmarks (ENV and GRE), can be concluded that traditional MACC, Taylor, Ward and EMAC methods are economically driven methods (Greedy methods), and that EMAC id the most greedy. In the other hand, GM is classified as an environmental friendly method. 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.

Table 1. Classification of GHG abatement measures ranking methods.

$\tau_{\mu 1}$	$\tau_{\mu 2}$	Kendall tau distance	Conclusion
MACC	GRE	$K(t_\mu, t_{GRE})$ closer to zero	Greedy
Taylor	GRE	$K(t_\mu, t_{GRE})$ closer to zero	Greedy
Ward	GRE	$K(t_\mu, t_{GRE})$ closer to zero	Greedy
EMAC	GRE	$K(t_\mu, t_{GRE})$ closer to zero	More Greedy
GM(1)	ENV	$K(t_\mu, t_{ENV})$ closer to zero	Environmentally friendly
GM(ε)	ENV	$K(t_\mu, t_{ENV})$ closer to zero	Environmentally friendly

10. Case studies; Comparison and discussions of results

To show the differences of the exposed methodologies with related applications found in the literature, we analysed the ranking proposed by Behrenz E. (2014) for the United Nations programme for the development of Colombia and the Final Report to the Committee on Climate Change for the Agriculture and Land Use, Land-Use Change and Forestry Sectors out to 2022, for the UK (Moran D. , y otros, 2008).

10.1 Report to the Committee on Climate Change out to 2022 for the UK (Moran D. , y otros, 2008).

The work developed by Moran, et al (2008) describes the derivation of traditional MAC curves to depict abatement potential for the agriculture, land use and land use change (ALULUCF) sectors in the UK from a bottom-up cost-effectiveness analysis of data on mitigation options within respective sectors. In the context of Colombia, Behrenz E. (2014) applied the MACC methodology for the main emitting sectors: waste, transportation, energy,industrial and residential sectors. For the purpose of this work, the results obtained for the industrial sector has been selected because it contains many negative cost mitigation measures, providing an illustrative scenario where MAC curves do not produce coherent results.

The values for the estimated CFP (central feasible potential) for 2022, Total Cost and Cost effectiveness used by (Moran D. , y otros, 2008) are exposed in Table 2.The comparison of the ranking produced by the traditional MAC method against the exposed methodologies is presented in Table 3. Note: The BOM ordered set is obtained from the ENV and Emac methods with $\alpha = 0.55$ (equation 11).

$$BOM^{\alpha}(ENV, EMac)(m) = 0.55 \cdot \tau_{ENV}(m) + 0.45 \cdot \tau_{Emac}(m) \qquad (11)$$

Table 2. 2022 abatement potential CFP (Moran D. , y otros, 2008).

Code	Measure	First Year Gross Volume Abated [ktCO2e]	Cumulative First Year Abatement [MtCO2e]	Cost	Cost Effectiveness [£2006/tCO2e]
AA	Crops-Soils-BiolFix	8.49	10.83	154,696.97	14,280.16

AK	Crops-Soils-SystemsLessReliantOnInputs	10.05	10.83	48,001.73	4,434.34
CA	BeefAn-Concentrates	80.96	10.82	29,249.60	2,704.54
AB	Crops-Soils-ReduceNFert	136.20	10.73	21,952.10	2,045.10
BH	DairyAn-Transgenics	504.29	10.60	17,924.19	1,691.28
AH	Crops-Soils-ControlledRelFert	165.90	10.09	10,778.82	1,067.95
AI	Crops-Soils-Nis	603.67	9.93	2,913.87	293.50
BG	DairyAn-bST	132.31	9.32	2,089.51	224.10
AF	Crops-Soils-SpeciesIntro	365.98	9.19	1,601.43	174.22
EB	OFAD-DairyMedium	44.12	8.83	212.71	24.10
EE	OFAD-BeefMedium	50.77	8.78	148.93	16.96
AC	Crops-Soils-Drainage	1,741.02	8.73	126.08	14.44
HT	CAD-Poultry-5MW	219.34	6.99	79.90	11.43
EC	OFAD-DairyLarge	250.81	6.77	53.89	7.96
EH	OFAD-PigsMedium	16.06	6.52	30.58	4.69
EF	OFAD-BeefLarge	97.79	6.50	16.39	2.52
EI	OFAD-PigsLarge	47.77	6.41	6.15	0.96
AM	Crops-Soils-SlurryMineralNDelayed	47.17	6.36	0.00	0.00
AO	Crops-Soils-UsingComposts	78.51	6.31	0.00	0.00
DA	Forestry-Afforestation	980.84	6.23	-44.37	-7.12
AD	Crops-Soils-AvoidNExcess	276.06	5.25	-264.07	-50.29
BB	DairyAn-MaizeSilage	95.98	4.98	-1,306.58	-262.63
AL	Crops-Soils-ImprovedN-UsePlants	331.80	4.88	-371.29	-76.10
BI	DairyAn-ImprovedFertility	346.26	4.55	-0.18	-0.04
BE	DairyAn-Ionophores	739.66	4.20	-204.13	-48.59
BF	DairyAn-ImprovedProductivity	377.36	3.46	-0.24	-0.07
AN	Crops-Soils-ReducedTill	55.77	3.08	-3246.31	-1,052.63
AE	Crops-Soils-FullManure	457.26	3.03	-451.05	-148.91
AJ	Crops-Soils-OrganicNTiming	1,027.16	2.57	-176.06	-68.48
AG	Crops-Soils-MineralNTiming	1,150.39	1.54	-159.62	-103.38
CG	BeefAn-ImprovedGenetics	46.32	0.39	-1,419.55	-3,602.93
CE	BeefAn-Ionophores	347.38	0.35	-606.48	-1,747.79

Table 3. Ordered measures for the 2022 abatement potential CFP of Moran, et al (2008).

Code	Measure	τ_{MAC}	τ_{Emac}	τ_{GRE}	τ_{ENV}	τ_{BOM}
AA	Crops-Soils-BiolFix	32	32	32	1	4
AK	Crops-Soils-SystemsLessReliantOnInputs	31	31	31	2	5
CA	BeefAn-Concentrates	30	30	30	3	7
AB	Crops-Soils-ReduceNFert	29	29	29	4	8
BH	DairyAn-Transgenics	28	28	28	5	10
AH	Crops-Soils-ControlledRelFert	27	27	27	6	11
AI	Crops-Soils-Nis	26	26	26	7	12
BG	DairyAn-bST	25	25	25	8	13
AF	Crops-Soils-SpeciesIntro	24	24	24	9	14
EB	OFAD-DairyMedium	23	23	23	10	15
EE	OFAD-BeefMedium	22	22	22	11	16
AC	Crops-Soils-Drainage	21	21	21	12	17
HT	CAD-Poultry-5MW	20	20	20	13	18
EC	OFAD-DairyLarge	19	19	19	14	19
EH	OFAD-PigsMedium	18	18	18	15	20
EF	OFAD-BeefLarge	17	17	17	16	21
EI	OFAD-PigsLarge	16	16	16	17	23

AM	Crops-Soils-SlurryMineralNDelayed	15	15	15	18	24
AO	Crops-Soils-UsingComposts	14	14	14	19	25
DA	Forestry-Afforestation	11	9	11	20	6
AD	Crops-Soils-AvoidNExcess	9	4	7	21	2
BB	DairyAn-MaizeSilage	4	2	3	22	1
AL	Crops-Soils-ImprovedN-UsePlants	7	3	6	23	3
BI	DairyAn-ImprovedFertility	13	13	13	24	27
BE	DairyAn-Ionophores	10	6	8	25	22
BF	DairyAn-ImprovedProductivity	12	12	12	26	29
AN	Crops-Soils-ReducedTill	3	1	1	27	9
AE	Crops-Soils-FullManure	5	5	5	28	26
AJ	Crops-Soils-OrganicNTiming	8	8	9	29	28
AG	Crops-Soils-MineralNTiming	6	10	10	30	31
CG	BeefAn-ImprovedGenetics	1	7	2	31	30
CE	BeefAn-Ionophores	2	11	4	32	32

The Kendall-Tau distance of the ordered sets exposed in Table 3, are compared to the ENV and GRE benchmarks (Figure 5). The dashed red line in Figure 5 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).

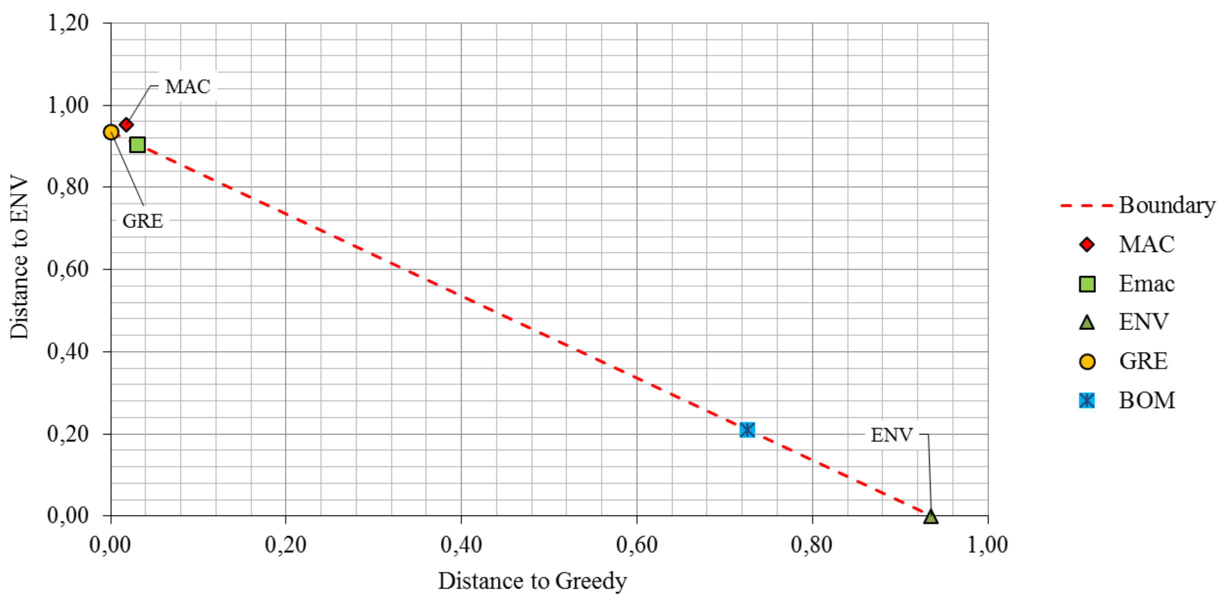

Figure 3 Kendall tau distance between the ordered sets exposed in table 3 compared to the ENV and GRE benchmarks

As can be seen on Figure 3, MAC is very close to GRE, this similarity highlight MAC (and its variations) weakness to rank negative cost measures. For example, MAC method ranks better CG measure than EN, been clearly EN a better option under both environmental and economic perspectives, EN has $Cost_m = -3246$ and $\Delta E_m = 3.08$, compared to GC with $Cost_m = -1419$ and $\Delta E_m = 0.394$. In this cases are recommended to use another approach to rank the negative cost measures, for example use Taylor to rank negative cost measures and MAC to rank the positive rank ones or use another alternative like EMAC or GM.

For this example, is computed the EMAC method for the project set. There is not an evident inconsistency in the produced ranking, but after computing Kendal-Tus distance is evident than EMAC is very close to GRE (like MAC), so, to achieve a more balanced method, ENV and EMAC are combined with $BOM^{0.55}$ resulting in a new method with an improved environmentalist perspective without neglect the economical perspective.

10.2 United Nations programme for the development of Colombia (Behrentz, 2014).

The study of abatement curves and mitigation potentials in the sectors of agricultural and livestock, transport, wastes, mining and energy developed by Behrentz (2014) exposes the cost effectiveness of different mitigation options in the Colombian context by applying the traditional MAC curves. The measures and values for the industrial sector used by Behrentz (2014) are exposed in table 4. Note: The BOM ordered set is obtained from the ENV and gre methods with $\alpha = 0.50$ (equation 12).

$$BOM^{\alpha}(ENV, GRE)(m) = 0.50 \cdot \tau_{ENV}(m) + 0.50 \cdot \tau_{GRE}(m) \tag{12}$$

Table 4. Abatement measures of the Industrial sector for Colombia (Behrentz, 2014) .

Code	Industry	Abatement Potential	Cost	Cost Effectiveness
M1	Energy use of solid-waste - transversal	69,000	160,00	2,32
M2	Recycling - transversal	55,000	230,00	4,18
M3	Direct reduction of iron ore with Hylsa technology	44,000	-965,00	-21,93
M4	Replacing coal with biomass - cement	43,000	-30,00	-0,70
M5	Reducing the proportion of clinker - cement	39,000	-15,00	-0,38
M6	CO2 capture and geological storage - cement	27,000	1260,00	46,67
M7	Improved efficiency of bagasse boilers - food and drinks	25,000	11,00	0,44
M8	Production change wet to dry process - cement	15,000	60,00	4,00
M9	Improving efficiency of oil-fired boilers - paper	5,000	-275,00	-55,00
M10	Improving efficiency of coal and diesel boilers - paper	3,000	-25,00	-8,33
M11	Improving efficiency of natural gas boilers - paper	2,000	-25,00	-12,50
M12	Improving efficiency of natural gas boilers - chemicals	1,000	-18,00	-18,00
M13	Improving efficiency of natural gas boilers - food and drinks	1,000	-20,00	-20,00
M14	Improving efficiency of LPG boilers - food and drinks	1,000	-20,00	-20,00
M15	Hydrogen recovery in ammonia production	0,400	13,00	32,50
M16	Improving efficiency of diesel-oil boiler - food and drinks	0,080	-9,00	-112,50
M17	Replacing coal with biomass - food and drinks	0,080	-0,60	-7,50
M18	Improving efficiency of oil-fired boilers - food and drinks	0,040	-2,00	-50,00
M19	Replacing coal with biomass - chemicals	0,030	-0,30	-10,00
M20	Improving efficiency of fuel-oil boiler - paper	0,020	-1,00	-50,00
M21	Replacing coal with biomass - paper	0,020	-0,10	-5,00

M22	Improving efficiency of LPG boilers - chemicals	0,010	-3,00	-300,00
M23	Improving efficiency of diesel-oil boiler - chemicals	0,002	-0,20	-100,00
M24	Improving efficiency of fuel-oil boiler - food and drinks	0,001	-0,10	-100,00

Table 5. Ordered mitigation options for the industrial sector in the Colombian context (Behrentz, 2014).

Code	Industry	τ_{MAC}	τ_{Emac}	τ_{GRE}	τ_{ENV}	τ_{BOM}
M1	Energy use of solid-waste - transversal	20	20	22	1	10
M2	Recycling - transversal	21	22	23	2	11
M3	Direct reduction of iron ore with Hylsa technology	9	1	1	3	1
M4	Replacing coal with biomass - cement	17	3	3	4	2
M5	Reducing the proportion of clinker - cement	18	4	9	5	3
M6	CO2 capture and geological storage - cement	24	24	24	6	17
M7	Improved efficiency of bagasse boilers - food and drinks	19	19	19	7	13
M8	Production change wet to dry process - cement	21	21	21	8	16
M9	Improving efficiency of oil-fired boilers - paper	5	2	2	9	4
M10	Improving efficiency of coal and diesel boilers - paper	14	5	4	10	5
M11	Improving efficiency of natural gas boilers - paper	10	6	4	11	6
M12	Improving efficiency of natural gas boilers - chemicals	10	9	8	12	7
M13	Improving efficiency of natural gas boilers - food and drinks	10	7	6	12	8
M14	Improving efficiency of LPG boilers - food and drinks	7	7	6	12	9
M15	Hydrogen recovery in ammonia production	23	23	20	15	22
M16	Improving efficiency of diesel-oil boiler - food and drinks	1	10	10	16	12
M17	Replacing coal with biomass - food and drinks	16	12	14	16	14
M18	Improving efficiency of oil-fired boilers - food and drinks	5	11	12	18	15
M19	Replacing coal with biomass - chemicals	13	15	15	19	19
M20	Improving efficiency of fuel-oil boiler - paper	2	14	13	20	18
M21	Replacing coal with biomass - paper	14	16	17	20	21
M22	Improving efficiency of LPG boilers - chemicals	7	13	11	22	20
M23	Improving efficiency of diesel-oil boiler - chemicals	3	17	16	23	23
M24	Improving efficiency of fuel-oil boiler - food and drinks	4	18	17	24	24

The Kendall-Tau distance of the ordered sets exposed in Table 5, are compared to the ENV and GRE benchmarks and represented in figure 6. The values of the traditional MAC observed above the dashed red line are far away from the ideal measures (zero distance to GRE and ENV). This implies that the ranking produced by traditional MAC could be replaced and improved by an alternative rank produced by BOM for some value of alpha.

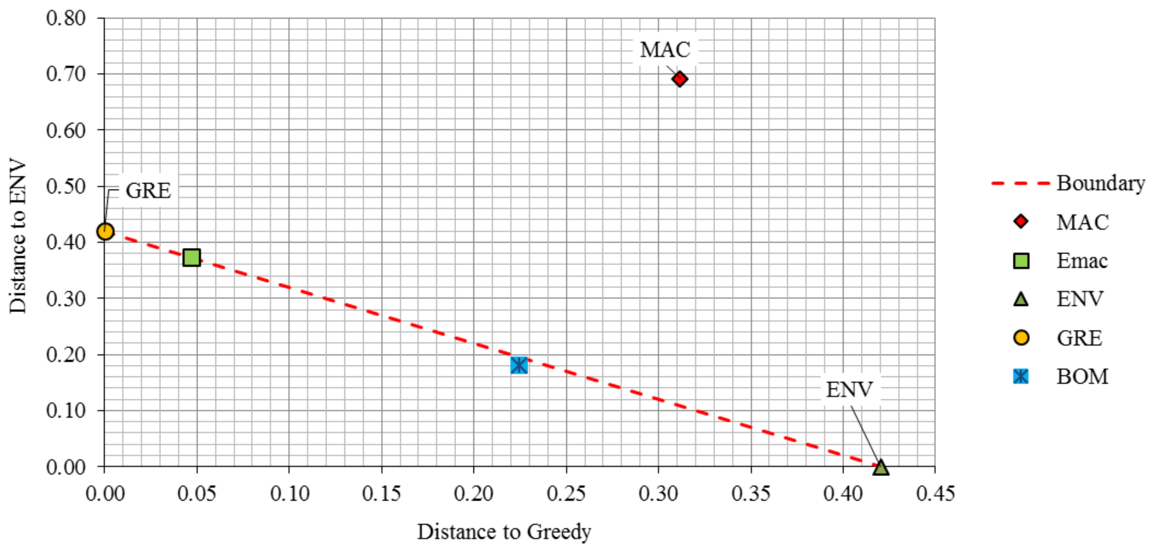

Figure 4. Kendall tau distance between the ordered sets exposed in table 8 compared to the ENV and GRE benchmarks.

Since in this example there are more measures with negatives cost, the erroneous ranking of MAC is more noticeable, for example the measure M16 which has $Cost_m = -9$ and $\Delta E_m = 0.08$ is ranked in first place and M9 with $Cost_m = -275$ and $\Delta E_m = 5$ is ranked sixth. In this case, oppositely to the results in the previous example, EMAC is very far away of MAC, and EMAC is no too close form GRE.

10.3 Discussion of results

In the Moran, et al. (2008) case study, the resulted measure applying MACC is CG (BeefAn-Improved Genetics) with an abatement potential of 0.39 tons of CO2 and a Cost of -1,419.55. Since, when applying the BOM method, the preferred measure is BB (DairyAn-MaizeSilage) with similar negative cost (-1,306.58) and nearly thirteen times of abatement potential (4.98). This second option is obviously better than the CG measure. Similarity, The Emac method ranked better the AN measure (Crops-Soils-ReducedTill) with a negative cost of -3,246.31 and an abatement potential of 3.08 tons of CO2, better values than the provided by the CG measure. Both the BB measure applying the BOM method (more ENV) or the AN measure applying the Emac method (more GRE) are better measures the one ranked by the traditional MAC.

For the Behrenz (2014) study, the EMAC method presents a more greedy and environmentalist rank than the traditional MAC, because the study includes many negative cost measures and the traditional MAC prioritises measures with low abatement potential and high negative costs. The $BOM^{\alpha=0.5}(Emac, ENV)$ ranking offers a balanced ranking between the ENV and GRE benchmark methods slightly under the boundary, implying that is better than any BOM combination of ENV and GRE. In this study, is noticed how the introduction of negative cost measures could affect the MAC ranking, MAC is much more distant to the reference methods and EMAC, and do not establish a clear perspective of what kind of projects is prioritizing. This implies than with more negative cost variables the error (or randomness) of MAC method increases.

11. Conclusions

As seen in this chapter, there are many methodologies to address the problem of ranking GHG abatement measures. Each one provides diverse results, which are appropriate in different situations. Then, is part of the decision maker liability to know and understand the methodologies for their purposes.

Traditionally, MAC curves one of the most used methodologies for evaluating which abatement options to implement by Governments through a comparison of their cost-effectiveness. However, in the last years some discrepancies have risen relating to its construction and interpretation. In particular, some authors have studied its failure for ranking negative cost measures. In this chapter, four alternative methodologies were exposed. (1) Taylor's method, (2) (3) The GM method (4) An extension of traditional MAC (EMAC method),

Is possible that none of the known methods will fit the decision maker´s necessities. For this reason, the combining methodology BOM is a better option. It allows decision makers to take into account the goodness of multiple methods in order to create new rankings adjustable to a specific GHG policy, whether it is fully or partially driven by economical or environmental positions.

Additionally to the ranking problems, decision makers need tools to compare and profile the variety of ranking methods. Kendal tau allow to measure the "distance" between two methods which indicates how similar they are, however this distance doesn´t give much information if it is computed between two regular methods. Then is advisable to compute this distance respect methods with known ranks. ENV and GRE are reference methods, been ENV the most environment friendly and GRE the most economical driven one, this reference methods and the Kendal tau distance allow to profile other methods.

12. Acknowledgements

The authors would like to thank the research group of Construction Engineering and Management (IN²geco) of Universidad de Los Andes.

13. Notations

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

Acronyms	Meaning
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 $m1$ and $m2$, and a balance α.
$Cost_m$	Total cost of the measure *m* ($Cost_m = \Delta C_m - \Delta B_m$)
ENV	Environmentalist benchmark.
GHG	Greenhouse gases

GM(ε)	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.
$\tau_{GM(\epsilon)}$	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 ε=1.
τ_{EMAC}	Set of ordered measures applying method Emac.
$K(\tau_{\mu_1}, \tau_{\mu_2})$	Kendall tau distance between methods μ_1 and μ_2.

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