Discussion of “Assessing temporal complementarity between three variable energy sources through correlation and compromise programming” F.A. Canales et al. Energy 192 (2020) 116637

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Abstract
This paper discusses the article “*Assessing temporal complementarity between three variable energy sources through correlation and compromise programming*.” The discussed paper proposes a novel method of assessing complementarity between three energy sources using correlation, compromise programming, and normalization. The method is then used to calculate a complementarity index which is applied to a case study in Poland. However, upon inspection, the normalization of the index overestimates the complementarity potential. This issue is discussed in detail in this paper, and an alternative way of calculating the index is proposed, eliminating the issue of overestimating complementarity.

Keywords
Energetic complementarity; renewable energy; hybrid power systems; correlation; variable renewables

1. Introduction
As evidenced and summarized in recent review papers [1]–[3], there is a current research interest and a growing body of literature discussing the concept of complementarity between renewable energy sources from various perspectives. Most theoretical works focus neither on specific resources nor the concept applicability but on how the complementarity can be quantified and compared. The most common metric for a pair of renewable sources to assess their complementarity is any variant of the correlation coefficient (Pearson, Spearman’s, Kendall’s, autocorrelation, cross-correlation) [2]. However, depending on the nature of the performed analysis, many other metrics and indices have been proposed, including the robust coefficient of variation, time-complementarity index [4],

wavelet-based complementarity index [5], and several metrics that assess the reliability of the cogeneration (e.g., Loss of load probability, Load tracking index, the stability coefficient, and others) [6].

On the other hand, the availability of complementarity metrics for n > 2 sources is limited. Borba & Brito [7] modified the index proposed in [4] to integrate partial indices measuring complementarity in terms of time, energy, and amplitude for more than two sources. Han et al. [8] evaluated the complementarity between solar-wind-hydro time series considering ramp and fluctuations within continuous time windows. The total variation complementarity index proposed by Cantor et al. [9], [10] measures the complementarity between multiple time series regarding a constant mean for each function. Finally, the method proposed by Canales et al. [11] combines correlation coefficients, compromise programming, and normalization to calculate a total temporal complementarity index k_t considering three renewable energy sources' time series. Recent studies have employed this latter method to estimate complementarity between three renewable sources [12]–[14].

The procedure described in [11] is based on well-known statistical and mathematical metrics. However, a closer inspection of the particular case when there is no correlation between the three data series (e.g., when the three are constant over the period) and results from Monte Carlo simulations indicate some limitations that could be addressed through an alternative normalization or interpretation of the total temporal complementarity index k_t, which corresponds to the final step of the method under discussion.

2. Discussion of the proposed index

The index proposed in [11] combines correlation coefficients, compromise programming, and normalization. A complementarity vector is constructed using pairwise correlation coefficients as

$$\boldsymbol{c} = \mathrm{cc}_{\mathrm{ws}}\widehat{ws} + \mathrm{cc}_{\mathrm{wh}}\widehat{wh} + \mathrm{cc}_{\mathrm{sh}}\widehat{sh} \tag{1}$$

where: cc_{ws}, cc_{wh} and cc_{sh} are the pairwise correlation coefficients of the time series of three energy sources, or in general, three different time series. In order to find out how well the three sources complement each other, compromise programming is used to find the distance between each point and the optimal solution, which in this application corresponds to perfect complementarity. This distance is calculated as

$$\mathrm{L_p}(\mathbf{c}) = \left[\sum_{k=1}^{n} \alpha_k^p \left|\frac{f_k^{best} - f_k(\boldsymbol{c})}{f_k^{best} - f_k^{worst}}\right|^p\right]^{1/p} \tag{2}$$

where: f_k^{best} is the optimal value, and f_k^{worst} the worst possible value. In the case of assessing complementarity using correlation coefficients, the optimal value is -1, and the contrary is 1. The parameter α_k^p denotes the weights for pairwise correlation coefficients. If all correlation coefficients are assumed equally important, $\alpha_k^p = 1$ for all cases. The authors of [11] suggest using $\mathrm{p} = 1$, which leads to a linear assessment of the results.

As is shown in [11], the minimal achievable value of $\mathrm{L_p}(\mathbf{c})$ is 0.75 for the three sources. When all pairwise correlation coefficients equal 1, the maximum value of $\mathrm{L_p}(\mathbf{c}) = 3$ is achieved. The proposed complementarity index, $k_t(\boldsymbol{c})$, is the normalization of metric $\mathrm{L_p}(\mathbf{c})$ calculated as

$$k_t(\boldsymbol{c}) = \frac{3 - L_p(\boldsymbol{c})}{2.25} \tag{3}$$

The reason that the index is normalized by 2.25 is the fact that $\mathrm{L_p}(\mathbf{c})$ can only take values in the set [0.75,3]. The normalized index $k_t(\boldsymbol{c})$, according to the authors of [11], should be interpreted as in table 1.

Table 1. Interpretation of complementarity index

Behavior	Correlation coefficient (CC) values (r_{xy} or ρ_s)	Normalization of the correlation coefficient [0,1]	Interpretation
Similarity	$0.9 \leq CC \leq 1.0$	$0.00 \leq Norm.(CC) < 0.05$	Very strong similarity
	$0.6 \leq CC < 0.9$	$0.05 \leq Norm.(CC) < 0.20$	Strong similarity
	$0.3 \leq CC < 0.6$	$0.20 \leq Norm.(CC) < 0.35$	Moderate similarity
	$0.0 \leq CC < 0.3$	$0.35 \leq Norm.(CC) < 0.50$	Weak similarity
Complementarity	$-0.3 < \mathrm{CC} < 0.0$	$0.50 \leq Norm.(CC) < 0.65$	Weak complementarity
	$-0.6 < \mathrm{CC} \leq -0.3$	$0.65 \leq Norm.(CC) < 0.80$	Moderate complementarity
	$-0.9 < \mathrm{CC} \leq -0.6$	$0.80 \leq Norm.(CC) < 0.95$	Strong complementarity
	$-1 \leq CC \leq -0.9$	$0.95 \leq Norm.(CC) \leq 1.00$	Very strong complementarity

2.1. Limitations of the proposed index

In the case of three uncorrelated series, such that the complementarity vector explained in equation (1) would be $\boldsymbol{c} = 0\,\widehat{ws} + 0\,\widehat{wh} + 0\,\widehat{sh}$, the obvious expected value of the complementarity index $k_t(\boldsymbol{c})$ should be 0.5 according to interpretation provided in table 1. This follows the logical reasoning that three completely uncorrelated series will expose neither complementarity nor similarity.

However, the metric $L_p(\boldsymbol{c})$ evaluated as in equation (2) would be 1.5, and as follows by equation (3), the complementarity index $k_t(\boldsymbol{c})$ evaluates to $2/3$ which implies moderate complementarity of the three uncorrelated series. This is further shown in figure 1, where three synthetic time series x, y, and z of length 1 000 are constructed using random numbers from a standard uniform distribution. Pair-wise correlation coefficients and the proposed complementarity index are calculated in 5 000 iterations. As expected, all pair-wise correlation coefficients are normally distributed with mean value $\mu = 0$, yet the complementarity index follows a normal distribution with $\mu = 2/3$.

The sampled correlation coefficient r will be approximately normally distributed with parameters [15]:

$$E(r) = \rho * \left(1 - \frac{1-\rho^2}{2n} + \cdots\right) \approx \rho \qquad (4)$$

$$\sigma^2(r) = \frac{(1-\rho^2)^2}{n} \qquad (5)$$

Since the complementarity index $k_t(\boldsymbol{c})$ is a linear function of the correlation coefficients as explained in equation (3), it will also be normally distributed. Scaling and addition of variables according to equation (3) yields the distribution parameters of $k_t(\boldsymbol{c})$ for the sampled correlation coefficients are

$$E\big(k_t(\boldsymbol{c})\big) = \frac{\sum_{k=1}^{3} \frac{-1 - E(r)}{-1 - 1}}{2.25} = 2/3 \qquad (6)$$

$$\sigma^2\big(k_t(\boldsymbol{c})\big) = 3\left(\frac{1}{2/2.25}\right)^2 \sigma(r) \qquad (7)$$

The expressions above match the distributions shown in figure 1.

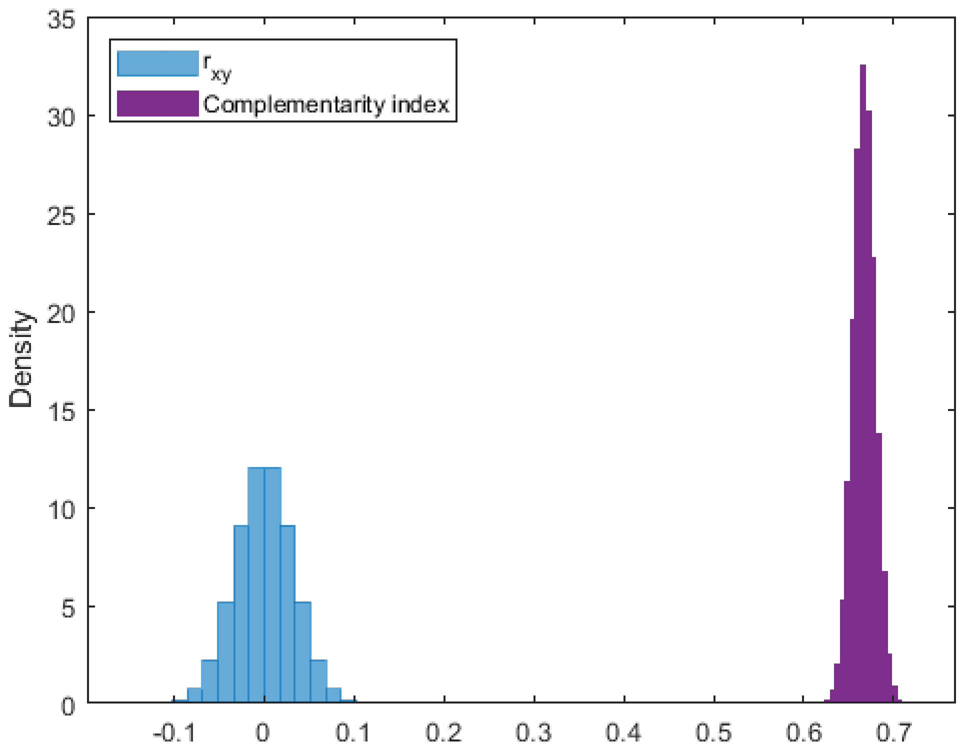

Figure 1. Monte Carlo simulations of the complementarity index

Following what has been presented, it is evident that the proposed index is skewed to imply complementarity when in fact, there should be neither complementarity nor similarity. This observation could be explained by the fact that not all combinations of correlation coefficients are possible when analyzing three time series. As previously explained, the minimum value of $L_p(\boldsymbol{c})$ is 0.75, which follows directly from what also is shown in [11], that for a set of three balanced sine functions, the minimum value of the correlation coefficients is $\rho \geq -0.5$. As a result, the input space is restricted, which in turn restricts the solution space of metric $L_p(\boldsymbol{c})$ and as follows $k_t(\boldsymbol{c})$.

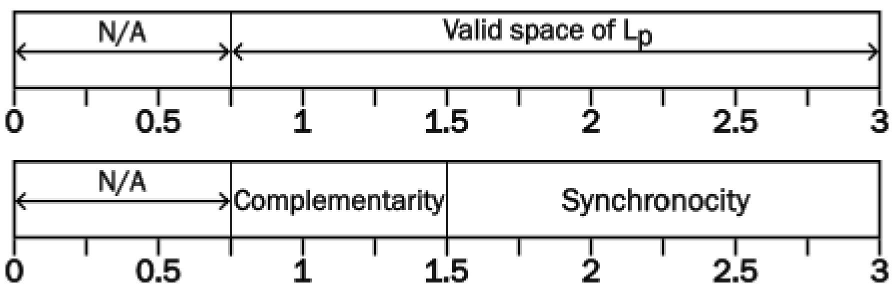

Figure 2. Visualization of restricted input and solution space

The normalization provided in equation (3) omits what is shown in figure 2 and instead assumes equal parts complementarity and synchronicity of the space of metric $L_p(\boldsymbol{c})$. As explained, this will lead to overestimation of complementarity when using the index.

2.2. Alternative normalization

In order to correct the overestimating behavior of $k_t(\boldsymbol{c})$ we propose an alternative normalization that accounts for the restricted solution space. The valid space of $L_p(\boldsymbol{c})$ is divided into complementarity and synchronicity regions, and the new proposed index is normalized as

$$k_1(\boldsymbol{c}) = \begin{cases} \dfrac{2.25 - L_p}{1.5} & 0.75 \leq L_p \leq 1.5 \\ \dfrac{3 - L_p}{3} & 1.5 < L_p \leq 3 \end{cases} \quad (8)$$

The index $k_1(\boldsymbol{c})$ can still be interpreted according to table 1. As can be seen in figure 3, the proposed index evaluates to 0.5 in the case of three uncorrelated time series. For the boundary cases of $L_p(\boldsymbol{c}) = 0.75$ and $L_p(\boldsymbol{c}) = 3$ the index $k_1(\boldsymbol{c})$ evaluates to the same values as previously proposed index $k_t(\boldsymbol{c})$.

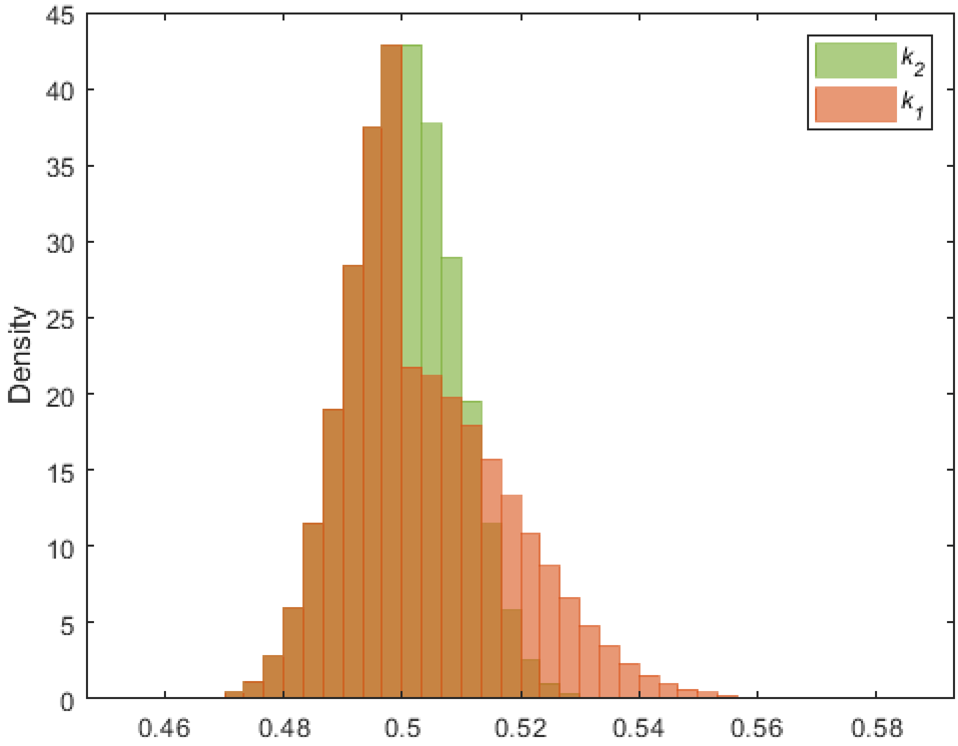

Figure 3. Monte Carlo simulations of the alternative normalization index for uniformly distributed random data

It can also be observed that since the normalization in equation (8) divides the normalization into two separate parts, the complementarity index $k_1(\boldsymbol{c})$ is not normally distributed for the sampled correlation coefficients.

However, it is possible to normalize $L_p(\boldsymbol{c})$ to calculate a complementarity index normally distributed with μ=0.5 for the sampled correlation coefficients, which requires a new interpretation of the index. By normalizing the $L_p(\boldsymbol{c})$ metric according to equation (9), the complementarity index can take values in the range [0, 0.75] and should be interpreted as in table 2.

$$k_2(\boldsymbol{c}) = \frac{3 - L_p(\boldsymbol{c})}{3} \quad (9)$$

Both the proposed normalization and interpretation do not alter the novel method presented in [11]; they only apply alterations to ensure a valid interpretation of the index. The difference between the two alternative normalization methods provided in this discussion is to either alter the calculated value of the index or the interpretation of the index. Both methods provide the same result and can be chosen based on presentation preferences.

Table 2. Alternative interpretation of complementarity index

Behavior	$k_2(\boldsymbol{c})$	Interpretation
Similarity	$0.00 \le k_2(\boldsymbol{c}) < 0.05$	Very strong similarity
	$0.05 \le k_2(\boldsymbol{c}) < 0.20$	Strong similarity
	$0.20 \le k_2(\boldsymbol{c}) < 0.35$	Moderate similarity
	$0.35 \le k_2(\boldsymbol{c}) < 0.50$	Weak similarity
Complementarity	$0.50 \le k_2(\boldsymbol{c}) < 0.575$	Weak complementarity
	$0.575 \le k_2(\boldsymbol{c}) < 0.65$	Moderate complementarity
	$0.65 \le k_2(\boldsymbol{c}) < 0.725$	Strong complementarity
	$0.725 \le k_2(\boldsymbol{c}) \le 0.75$	Very strong complementarity

2.3. Implications of new indices

A case study has been conducted to clearly show the implications and differences between the previously and newly proposed indices. The original and proposed indices have been calculated for time series of average monthly solar net radiation, surface runoff, and windspeed for the continental territory of Colombia. The data used for calculating the indices is the same employed in the original method article of the previously proposed index [14].

Table 3. Summarized results of the indices.

	$k_t(\boldsymbol{c})$	$k_1(\boldsymbol{c})$	$k_2(\boldsymbol{c})$
Very strong similarity	0.00%	0.00%	0.00%
Strong similarity	0.00%	0.00%	0.00%
Moderate similarity	0.40%	1.44%	1.44%
Weak similarity	1.44%	4.51%	4.51%
Weak complementarity	3.42%	9.97%	9.97%
Moderate complementarity	20.09%	48.75%	48.75%
Strong complementarity	74.29%	35.26%	35.26%
Very strong complementarity	0.36%	0.06%	0.06%

The spatial distribution is presented in figure 4. Table 3 summarizes the percentage of land area where the corresponding index implies similarity or complementarity. As can be seen in both figure 4 and table 3, the previously proposed index $k_t(\boldsymbol{c})$ are overestimating the complementarity potential as previously discussed, and the indices $k_1(\boldsymbol{c})$ and $k_2(\boldsymbol{c})$ lead to identical suggestion of complementarity potential.

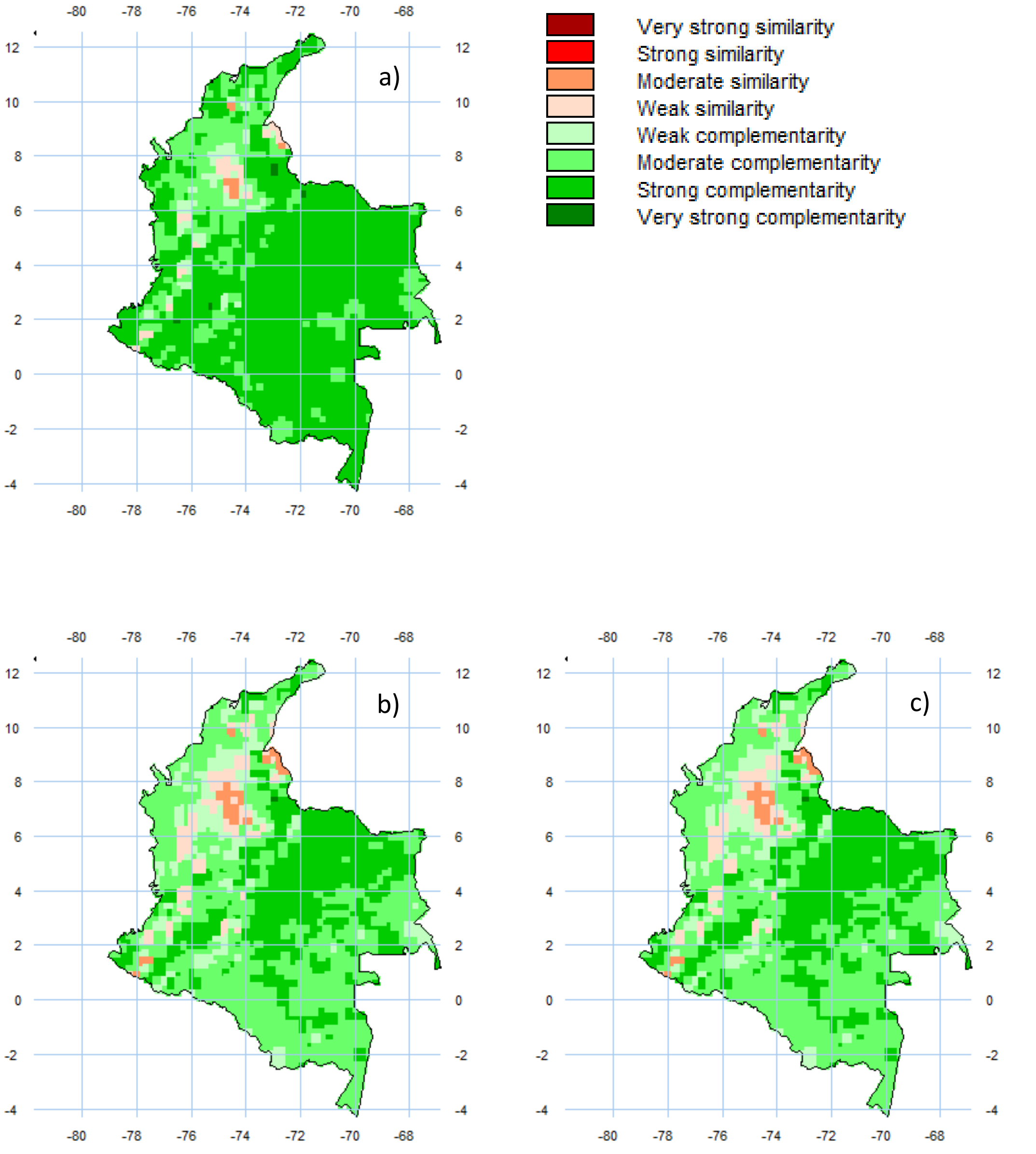

Figure 4. Complementarity between solar radiation, surface runoff, and wind speed in Colombia according to the a) original index k_t, b) k_1, and c) k_2.

Conclusions

The index proposed in [11] overestimates the complementarity due to the neglect of the restricted solution space. By applying the normalization explained in this discussion, the index can be implemented without overestimating complementarity. The proposed index $k_1(\boldsymbol{c})$ ranges from 0 to 1 but is not symmetric for the sampled correlation coefficients, whereas index $k_2(\boldsymbol{c})$ is symmetric but ranges from 0 to 0.75. Index $k_1(\boldsymbol{c})$ interpreted as in table 1 yields the same results as index $k_2(\boldsymbol{c})$ interpreted as in table 2 so the choice of which index to use is a matter of preference for data visualization.

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