Implementation of Environmental Decision Making Tool For Renewable Energy Utilization: A Case of Wind and Solar

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Abstract: In this paper, an Environmental Decision Making Tool with Renewable Energy (EDMTRE) is proposed with the resources cost as constraints. Modifed ReCiPe Version 1.3 Model is adopted to represent the midpoint indicators. A three-method hybrid; Modified Firefly Algorithm with Levy Flights and Derived Mutation (MFA-LF-DM) with parameters brightness, distance, attractiveness, movement, randomness reduction and mutation is used to validate the EDMTRE on IEEE 30-unit system. The levy flights reduce the random movement of the objective function while the derived mutations are improve the exploration of the candidate solution. The uncertainties and variability of the renewable sources are modelled using Structural Path Analysis (SPA). The results are analyzed under optimal emissions, health and ecosystems end points. From the simulated mid-point indicators, it is apparent that the deployment of RE results in more accurate environmental emissions when the resource cost is constrained. Further, the effects of PV technology to the environment are four times more adverse compared to wind.

Key Words: Environmental Decision Making Tool with Renewable Energy (EDMTRE), mid-point indicators Modified Firefly Algorithm with Levy Flights and Derived Mutation (MFA-LF-DM), Modifed ReCiPe Version 1.3 Model, Renewable Energy (RE), Structural Path Analysis (SPA)

I: INTRODUCTION

The adverse environmental effects of Non-Renewable energy (NRE) are global concerns [1-3]. The signing of the Kyoto protocol has led to many states across the globe to commit to replace these fuels by the *"free and cleaner"* renewable energy technology (RET) for energy production. However, global attention has majorly focused on the hostile impacts of the NRE to the environment ignoring the RET. According to Abbasi et al. [4], all public discussions held regarding pollution from CSE recommend that everyone should adopt RETs for *"clean, harmless and free"* energy production. But with the rising percentage of RE in global energy mixing, serious research efforts should be given to investigate whether RET sources are as clean and harmless as they are traditionally believed to be. Much research effort has been put on combined economic emission dispatch (CEED), however, RET has not fully penetrated the market due to several barriers, one of which is their perceived negative environmental impacts [5]. These include Health, Ecosystems and Resources cost [6]. In order to ensure sustainability of RE over time, these end point environmental impacts must be considered in the design and installation of RETs so as to determine its viability in a particular area.

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Instead, these tools use the capital costs, operation and maintenance costs and annual replacement costs and the perceived reduction in three main emissions (CEED) to calculate the OCE and emissions [7]. This is not accurate and realistic. This paper proposes a *Modified ReCiPe Model* which incorporates the industrial process inputs, outputs and their technical modelling in terms of input, endpoint and midpoint indicators respectively.

A: Contribution: The objective of this paper is to develop, for the first time, an Environmental Decision Making Tool with Renewable Energy (EDMTRE) using the midpoint indicators of the Modified ReCiPe Version 1.3 Model to represent the negative environmental effects. Positive impacts of RETs on health and ecosystem are included in the EMDTRE using the more accurate cubic cost function [2]. A three method hybrid Modified Firefly Algorithm with Levy Flights and Derived Mutation (MFA-LF-DM) is employed for the first time for the solution while the uncertainties of RE are modelled using Structural Path Analysis (SPA).

II: MODIFIED $ReCiPe$ MODEL

$ReCiPe$ is a Life Cycle Impact Assessment (LCIA) method for RE released in 2008 by Heijungs et al. [8]. In this paper, ReCiPe Version 1.3 Model is adopted, which has optimal emissions reduction, input, and midpoint and endpoint indicators. The inputs considered in this model include the raw materials , land use, the optimized emissions by using RE (NO_X , SO_2 and CO_2) , VOS, P,CFC, Cd, PAH, DDT etc. The output is the end point categories which include reduced major emissions, Human health, Ecosystems and Resources cost. The midpoint indicators for each end point stated above include the following:

i) *Optimal Emissions Reduction (OER):* This models the three main Health and Ecosystems benefits of RETs. The benefits modelled include reduction in H_{11} (Ozone Depletion) related toNO_X, $\mathrm{H}_{66}/\mathrm{E}_{11}$(Climate Change/Global Warming Potential) linked to the CO_2 E_{22}(Terrestrial acidification) associated withSO_2.
ii) *Human Health:* Ozone depletion, Human Toxicity, Radiation, Photochemical Oxidant formation, Particulate formation and Climatic change
iii) *Ecosystem:* Climate change, Terrestrial ecotoxicity, Terrestrial acidification, Agricultural land occupation, Natural land transformation, Marine ecotoxicity, Marine eutrophication and Fresh water ecotoxicity
iv) *Resources Cost:* Fossil fuel consumption, mineral consumption and water consumption etc. In this paper, this is treated as a

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constraint in the Optimal Emissions Objective for two reasons; for simplicity and to give due attention to the environmental concerns.

There are twenty One (21) midpoint impact categories and Four (4) endpoint impact categories in the Modified *ReCiPe* Model. Characterization factors are used to convert emissions to the units of the midpoint impact categories, and from midpoint to endpoint. The goal of *Modified ReCiPe Model* is to harmonize midpoint and endpoint impact categories in a single framework with both environmental benefits and hazards weighed against each other. This method builds on the previously existing Recipe Centrum Milieukunde Leiden (CML 2002) and Eco-indicator 99 methods, the latter of which methodology uses the endpoint approach, and the former, midpoint [8].

A: Mid-Point Versus End-Point Approach

There are both merits and demerits of using midpoints and endpoints. Midpoints are generally fairly accurate, but the units, usually in terms of a reference compound, can render it difficult for the analyst or a policy maker to understand the overall impact. In the other hand, endpoints are much easier to conceptualize since they are expressed in terms of tangible effects using a point system, dollar amounts, number of species affected, or number of human life years lost (DALY), to which it is easier to relate. However, the method of translating the midpoint impacts to endpoint units incorporates much uncertainty. This uncertainty stems from poor understanding of the mechanisms through which pollutants affect ecosystems and human life and the dependence these mechanisms may have on geographical factors. Thus, the tradeoff between result accuracy and result interpretation becomes quite evident. In this paper, accuracy in detection of environmental effects is our concern hence the midpoint approach is adopted.

III: ENVIRONMENTAL DECISION MAKING TOOL FOR RE (EMDTRE)

A: Emissions Optimization by Using RE with Cost Constraints (EORECC)

A single objective emissions reduction function (SOERF) based on the relation [9]

$$\mathrm{E}(P_{i,j,k})\beta_{3,i}P_{t,i}^{3}+\beta_{2,i}P_{t,i}^{2}+\beta_{1,i}P_{t,i}^{1}+\beta_{0,i} + \zeta_{3,i}\exp(\lambda_{3,i}\ P_i)+\zeta_{2,i} \quad (1)$$

where $\mathrm{E}(P_{i,j,k})$ is the Emissions Reduction Impact Index (ERII) in ton/h whose cost implication can be calculated using an Environmental Cost Factor (ECF). Further, $\beta_{3,i}, \beta_{2,i}, \beta_{1,i}$ *and* $\beta_{0,i}$ are the emissions coefficients of the i^{th} unit while $\zeta_{3,i}$ and $\lambda_{3,i}$ are the emission factors due to the ramping effect of i^{th} unit. $\zeta_{2,i}$ The three main emissions that are considered include NO_X, SO_2 and CO_2 for the power plants in the SOERF. The emissions objective function, E, is formulated as

$$\mathrm{EORECC}=\mathrm{E}(P_{i,j,k})=\sum_{l=1}^{G}E(P_{i,t,s},P_{j,t,s},P_{k,t,s}) \quad (2a)$$

$$G=T+W+S \quad (2b)$$

where G is the total number of thermal (T), wind (W) and solar (S) generators in the system. The cost will treated as a constraint. EORECC represents the positive impacts of RETs which has been well explored in past literature [17].

B: *Environmental Decision Making Tool for Health and Ecosystems (EDMTHC)*

The process output G_i can be defined by the relation

$$G_i = AG_i + P_D \quad (3)$$

where A is inter industry requirements matrix and P_D is the power demand. From equation (3), the process output G_i can be written as

$$G_i = (1-A)^{-1}\ P_D = LP_D \quad (4)$$

where L the Leontief inverse defined by $L=(1-A)^{-1}$ denotes the inclusion of the environmental conditions(s) into the industrial processes.

The environmental effects $e(G_i)$ is then defined as

$$e(G_i) = SG_i \quad (5)$$

with S being a Stressor matrix while $e(G_i)$ represents both Health (H) and Ecosystems (E) impacts of RETs.

The total environmental impact $E(G_i)$ is finally represented by

$$EDMTHC = E(G_i) = Ce(G_i) \quad (6)$$

with C being the characterization factor.

C: Environmental Decision Making Tool with RE (EDMTRE)

Using equations (1) and (6) for the EORECC and EDMTHC respectively, Environmental Decision Making Tool with RE (EMDTRE) can be formulated as

$$EMDTRE = \mathrm{E}(P_{i,j,k}) + hE(G_i) \quad (7)$$

where h is the weighting factor for the positive and negative impacts of RETs.

D: Resource Cost Constraints (RCC):

The EMDTRE is solved subject to the following *Resource Cost Constraints (RCC):*

a) *Thermal Cost Constraint(TCC)* [12]

$$\mathrm{F}(P_{ij}) \geq \left\{a_{0,i}+\sum_{j=1}^{L=n}a_{ji}\,P_{t,i}^{j}+r_i\right\}+\left|e_i\sin f_i(P_i^{min}-P_i)\right| \quad (8)$$

where $a_{0,i,}a_{j,i}, e_i$ and f_i are the cost coefficients of the i^{th} unit, $P_i^{min}$is the lower generation bound for the i^{th}unit and $r_i$is the error associated with the ith equation.

b) Wind Cost Constraint(WCC) [17]

$$F(w_{ij}) \geq F_{wi}(w_{ij}) + F_{p,wi}(w_{ij,av} - w_{ij}) + F_{r,wi}(w_{ij} - w_{ij,av}) \quad (9)$$

where w_{ij} is the scheduled output of the i^{th} wind generator in the j^{th} hour, $F_{wi}(w_{ij})$ is the weighted cost function representing the cost based on wind speed profile, $F_{p,wi}(w_{ij,av} - w_{ij})$ is the penalty cost for not using all the available wind power and $F_{r,wi}(w_{ij} - w_{ij,av})$ is the penalty reserve requirement cost which is due to the fact that that actual or available power is less than the scheduled wind power.

c) *Solar Cost Constraint (SCC)* [17]

$$F(PV_{ij}) \geq F(PV_{ij}) + F_{p,PVi}(PV_{ij,av} - PV_{ij}) + F_{r,PVi}(PV_{ij} - PV_{ij,av}) \quad (10)$$

where $F_{PVi}(PV_{ij})$ is the weighted cost function representing cost based on solar irradiance. The other two are the respective penalty costs with respect to the definition in expression (9) but now applied to the PV sources. It is worth to note that if the actual renewable power is more than the scheduled, then the reserve requirement cost is reduced to almost a negative meaning a reduction in cost of RE.

IV: PROPOSED HYBRID METHODOLOGY

The hybrid method consists of Modified Firefly Algorithm (MFA) with Levy Flights (LF) and Derived Mutation (DM) [MFA-LF-DM] and Structural Path Analysis (SPA). These are discussed in the next sub sections.

A: Modified Firefly Algorithm (MFA) with Levy Flights (LF) and Derived Mutation (DM) [MFA-LF-DM]

The fireflies are the most charismatic species among the insects and their spectacular display have inspired the poets, writers and scientists. Today more than 2000 species exists and the flashings of the fireflies can be seen in the summer sky in the tropical and temperate regions with warm weather and most active in the nights [9]. These fireflies produce the short rhythmic patterns of flashing lights and these patterns of flashes are unique for a particular species, and the flashing light is produced by a *bioluminescence* process. However the flashing lights obey certain physical rules, the light intensity, *I*, decrease with the increase of distance *r* according to the term $I\alpha 1/r^2$ [10]. The purposes of the flashing include Mating, Communication and Feeding.Some of the flashing characteristics of fireflies can be idealized so as to develop firefly-inspired algorithms. The flashing light can be formulated in such a way that it is associated with the objective function to be optimized (EMDTRE in this case). This makes it possible to formulate firefly algorithm (FA).

Firefly Algorithm (FA) [11] is a new nature inspired algorithm developed by Xin-She Yang in the year 2007, based on the flashing behavior of the fireflies. The flashing signifies the signal to attract other fireflies, where the *objective function* is associated with the flashing light or the light intensity which helps the fireflies to move to brighter and more attractive locations to achieve optimal solution.

In this paper, MFA-LF-DM is proposed as it outperforms the more popular Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) since it *converges more quickly avoiding the problem of premature convergence at the same time* ,deals with global optimization more naturally, more efficient and has higher success rates. The method can handle NP Hard Problems and further, it is well fitted for the intermittent search strategy [9]. A NP hard problem is a problem which cannot be solved in polynomial time due to its complexity. Such a problem cannot be solved in definite steps of a pure algorithm. EMDTRE in this case fall in this category.

The MFA-LF-DM used in this paper has six operators. These include brightness, distance, attractiveness, movement, randomness reduction and mutation [12]. These are explained and formulated as follows:

i) Brightness

In the simplest case for maximum optimization problems, the brightness I of a firefly at a particular location x can be chosen as

$$I(x) \propto f(x) \quad (11)$$

This can further be expressed by the inverse square law

$$I(r) = \frac{I_0}{r^2} \quad (12)$$

where $I_0$the brightness intensity at the source (original light intensity) and r is the distance between any two fireflies. $I(r)$ decreases with distance from its source. Light is also absorbed in the media. Thus, attractiveness should be allowed to vary with the degree of absorption. For a given medium with fixed absorption coefficient (γ), then

$$I(r) = I_0 \exp(-\gamma r^2) \quad (1$$

ii) Distance

The distance between any two fireflies i and j at positions x_i and x_j respectively is the Cartesian distance

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \quad (14)$$

Where $x_{i,k}$ is the k^{th} component of the spatial component x_i of the i^{th} firefly, d is the number of problem dimensions.

Instead of the basic, Cartesian distance r_{ij} , the first modification of the basic FA is done by finding $r_{ij(\min)}$ which is the minimum variation distance between the i and j fireflies. The minimum distance between any two fireflies i and j at x_i and x_j is thus given by

$$r_{ij(\min)} = \min r_{ij} = \min\|x_i - x_j\| \quad (15)$$

However, the calculation of distance $r_{ij(\min)}$ can also be defined using other distance metrics, based on the nature of the problem, for example Manhattan Distance, etc.

iii) Attractiveness

The attractiveness (β) of fireflies is proportional to the light intensity (I) seen by the adjacent fireflies .Thus

$$\beta(r) \propto I(r) \quad (16)$$

The attractiveness β is relative and it should be seen in the eyes of the beholder or judged by other fireflies, and thus it should vary with$r_{ij(\min)}$. Thus, the attractiveness β between two fireflies i and j at a separation distance $r_{ij(min)}$ is given by

$$\beta = \beta_0 \exp(-\gamma r^2) \quad (17)$$

where β_0 is the attractiveness at $r = 0$ and $r = r_{ij(min)}$ for simplicity. In most cases of implementing FA, $\beta_0 = 1$. Further γ is the absorption coefficient that controls the decrease in light intensity. In actual implementation, the actual implementation $\beta(r)$ is a *monotonically decreasing function* generalized as

$$\beta = \beta_0 \exp(-\gamma r^m) \quad m \geq 0 \quad (18)$$

For a fixed γ the characteristic length becomes

$$\Gamma = \gamma^{-1/m} \rightarrow 1 \; as \; m \rightarrow \infty \quad (19)$$

Conversely, for a given length scale, Γ is an optimization problem and the parameter γ can be used as a typical initial value, that is,

$$\gamma = \frac{1}{\Gamma^m} \quad (20)$$

Theoretically $\gamma \in [0, \infty]$. Thus, there are two asymptotic cases [12]:

Case 1: $\gamma \rightarrow 0$. In this case $\beta = \beta_0$ and $\Gamma \rightarrow \infty$. This corresponds to a special case of *Particle Swarm Optimization (PSO)* in terms of optimal solution and efficiency.

Case 2: $\gamma \rightarrow \infty$. In this case $\beta(r) \rightarrow \delta(r)$, the dirac delta function and $\Gamma \rightarrow 0$. This is completely identical to *Random Search Method (RSM).*

In most practical applications, $0.01 \leq \gamma \leq 100$[13] and is determined by the characteristic length Γ of the system to be optimized.

iv) Movement

The movement of a firefly i is attracted to another more attractive (brighter) firefly j by the relation

$$x'_{i+1} = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_i - x_j) + \alpha \,\mathrm{sign}\left[rand - \frac{1}{2}\right] \quad (21)$$

where x_i is the current position of the firefly i , the second term defines the fireflies attractiveness to light intensity as seen by the adjacent firefly j and the third term is for the random movement of a firefly if no brighter firefly is left, α is a randomization parameter determined by the problem of interest usually $\alpha \in [0,1]$ and $rand$ is a random number generator uniformly distributed over the space [0, 1], that is,$rand \in [0,1]$, [13]

In general, the solutions can be improved by reducing the randomness by

$$\alpha = \alpha_\infty + (\alpha_0 - \alpha_\infty)e^{-t} \quad (22)$$

where $t \in [0, t_{max}]$the pseudo is time for simulation and t_{max} is the maximum number of generations, α_∞ and α_0 are the final and initial values of the randomness parameter.

Thus, the parameter setting for α can be expressed by

$$\alpha_t = \alpha_0 \delta^t \quad 0 < \delta < 1 \quad (23)$$

where α_t controls the randomness and the diversity of the solution, α_0 is the initial randomness scaling factor and δ is the cooling factor. For most applications,$0.95 < \delta < 0.97$. This can be tuned during iterations so that the α_t varies with the iteration counter$t$.

If we let Γ to be the average scale of the problem of interest (that is, EMDTRE in this case), then initially,

$$\alpha_0 = 0.01\Gamma \quad (24)$$

The number 0.01 comes from the fact that random walk requires a number of steps to reach the target while balancing the local exploitation without jumping too far in a few steps.

It is a good idea to replace α by $\alpha = \alpha S_k$ where the scaling parameters $S_k(k = 1 \ldots . d)$in the d dimensions should be determined by the actual scales of the problem of interest (EDMTRE in this case).

v) Randomness Reduction

Levy Fight (LF) is a random walk of step lengths having direction of the steps as isotropic and random. The concept propounded by Paul Pierre Levy (1886-1971) is very useful in stochastic measurements and simulations of random and pseudo-random phenomena.

The movement of a firefly i with Levy Flights (LF) is defined by the relation

$$x'_{i+1} = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_i - x_j) + \alpha \,\mathrm{sign}\left[rand - \frac{1}{2}\right] \oplus \mathrm{Levy} \quad (25)$$

where the second term is due to attraction, while the third term is randomization via the Levy Flights(LF) with α being the randomization parameter. The product $\oplus$ means entry wise multiplication.The sign $\left[rand - \frac{1}{2}\right]$ where $rand \in [0,1]$ essentially provides a random sign or direction while the random step length is drawn from a Levy distribution given by

$$Levy \sim u = t^{-\lambda} \; (1 < \lambda \leq 3) \quad (26)$$

which has an infinite variance with an infinite mean. The levy flights are used to *improve the tuning of the control parameters and to ensure a higher convergence rate.*

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vi) Derived Mutation (DM)

To further improve the exploration or diversity of the candidate solution, the simple mutation corresponding to α from the ant colony optimization (ACO) genetic algorithm (GA), evolutionary programming (EP) and differential evolution (DE) algorithms is adopted in the MFA-LF process. This enhances the accuracy of the optimum results in solving the EMDTRE problem. This is the second major modification made to the traditional FA. The proposed MFA-LF-DM is implemented as in [12].

Each *Firefly* is represented by a v*ector of generator power outputs (that is potential solution)*. In most applications a populations size of fireflies between $15 < n < 100$ is used, however the best range is $25 < n < 40$. for maximization problem, the brightness is simply proportional to the value of the fitness or the objective function. For Simplicity, attractiveness of fireflies is determined by its brightness or light intensity which in turn is associated with the encoded objective function (EMDTRE in this case). The *light intensity* of each Firefly is the *problem objective function (EMDT in this case).* The FA parameters used in the EMDTRE problem are as shown in Table 1.The mapping of the parameters to the EMDTRE problem is also given.

TABLE 1:MFA-LF-DM PARAMETERS

Parameter	Range	Parameter value
Brightness		EMDTRE
Firefly		Mid-Point Indicators
Number of fireflies (n)	$15 < n < 100$	50
Alpha (α)	$\alpha \in [0,1]$	0.9
Beta (β)		0.5
Gamma (γ)	$0.01 \leq \gamma \leq 100$	1.0
Maximum number of iterations		100
Attraction at $r = 0, (\beta_0)$	$\beta_0 = 1$	1.0
Lambda (λ)	$1 < \lambda \leq 3$	1.5

B: Structural Path Analysis (SPA): Structural Path Analysis (SPA) is performed using the code developed by Glen Peters and Edgar Hertwich [14-15] and modified b Yasushi Kondo] 16]. The code is further modified in the EMDTRE model proposed in this paper to allow the export of the simulated mid-point and end point results directly to Excel. The code explores paths with a length up to the maximum number of tiers set by the user and has a contribution to the total emissions or impact greater than or equal to the user-defined tolerance. The code further sorts the paths found in order of decreasing contributions, and outputs the number of paths satisfying the conditions set by the user. Additional output includes the sorted list of paths, the nodes of each path, the path length and the path contribution to overall optimal emissions or health-ecosystem impact. The tolerance was set to 0.005%, and the maximum number of tiers was set to 15.

V: RESULTS AND DISCUSSIONS

In this paper, IEEE 30 Bus system is used as the test case, where modification is done to include wind and solar generations at maximum 30% penetration [12]. The installed capacity for each of the RE sources is 60MW, the other parameters of the wind(W) and solar (S) are as in [18]. Thermal (T) case is taken as the base system. Three categories of results are presented; Emissions Optimization, Health and Ecosystems effects.

A: Emissions Optimization by Using RE with Cost Constraints (EORECC)

The nominal load (NL) for the system is 290MW. Loading at 80% and 120% of the NL are also considered for comparison. Emissions without cost constraints are presented in Table 2 while those with thermal and RE cost constraints are as in Table 3. Comparing the two cases, it is clear that cost constraints increases the emissions levels by 36.1% but results to a decrease in resources cost by 19.2%. Thus, a more accurate determination of optimal emissions is including the resources cost as a condition. Such a tradeoff between emissions and cost is paramount due to the increased environmental concerns. The optimal emissions levels can then be applied to evaluate the Health and Ecosystems endpoints for they are responsible for Ozone depletion, Climate change and Terrestrial acidification. It is worth to note that in Table 3, emissions reduce by 5.97% with increased load above the NL level.

TABLE 2: EMISSIONS OPTIMIZATION WITHOUT COST CONSTRAINTS

	80%NL	NL	120% NL
Emissions, E(Ton/h)	0.9577	0.9524	0.9532
COST ,C($/h)	1504.24	1647.01	1776.17

TABLE 3: EMISSIONS OPTIMIZATION WITH COST CONSTRAINTS

	80%NL	NL	120% NL
Emissions, E(Ton/h)	1.2921	1.2962	1.2188
Cost ,C($/h)	1177.50	1331.03	1447.07

B: Health End Point Impacts (HEPI)

The mid-point indicators for Human Health (H) considered in this paper include the following: H_1: Ozone depletion (Ton/h), H_2:Human Toxicity, H_3:Ionizing Radiation, H_4:Particulate Matter [PM] Formation, H_5:Photochemical Oxidation Formation [PCOF](Ton/h) and H_6/E_1:Climate change / Global Warming Potential [GWP] (Ton/h).

The simulated results are as shown in Table 4. From the table, use of PV increases H_1 by 126% while wind reduces the same by 67.3%. H_1 (Ozone Depletion) is closely related to the NO_X emissions and with solar, this increases due to the combustion of fossil fuels. Use of RE sources reduces H_2(Human Toxicity) by 91.8% for wind and 69.5% for solar respectively. It is worth to observe that the use of Wind in a pure thermal system reduces H_3(Ionising Radiation) by 79.6% while PV technology increases the same by 38.6%. Solar adds four times more of H_4(Particulate Matter [PM]) relative to wind. This is due to two reasons; the PV manufacturing process where there is incomplete combustion of fossil fuels and the wafer-sawing process which creates fine silicon dust particles.RE

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deployment reduces H_5 (Photochemical Oxidation Formation) [PCOF] significantly. Solar contributes the highest to H_6/E_1(GWP/CC) while wind is the lowest.This is due to the energy-intensive silicon purification process where more fossil fuels (with carbon) are combusted. It is worth to note that the midpoint impact category of "climate change" contributes to both the damage to "human health" and damage to "ecosystems" endpoint categories.

TABLE 4: HEALTH EFFECTS END POINTS

Source /Parameter	T	W	S
H_1	1.8549	0.6059	4.1851
H_2	91.5034	7.5389	27.8809
H_3	4,906.2323	1,003.34	6,800.98
H_4	3,895.1502	22.5611	39.5767
H_5	0.7301	0.0026	0.0082
H_6/E_1	0.3054	0.0099	0.0016

C: Ecosystems End Point Impacts (EEPI)

The mid-point indicators for Ecosystems effects (E) include H_6/E_1:Climate Change/Global Warming Potential [GWP] (Ton/h), E_2: Terrestrial acidification (Ton/h),E_3: Terrestrial Eco-toxicity (Toh/h), E_4 : Marine Eco-toxicity (Ton/h), E_5: Marine eutrophication and fresh water Eco-toxicity (Ton/h),E_6:Land Occupation [LO] ($km^2.a$) and E_7:Land Transformation [LT] (km^2). The results for the thermal (T), wind (W) and solar (S) generators in the system bare as shown in Table 5. With the thermal base, wind technology reduces E_1 by 91.2% , E_2 by 95.9%, E_3 by 56.95%, E_4 by 77.1% , E_5 by 97%,E_6 by 91.3% and finally E_7 by 84.12%. Such effects are lower with the PV technology, however, it is significant to note that E_3 (Terrestrial Eco-toxicity) increases by 856.7%.

TABLE 5: ECOLOGICAL EFFECTS END POINT

Source /Parameter	T	W	S
E_1	0.3053	0.0096	0.0026
E_2	1.3055	0.0053	0.1151
E_3	0.0045	0.0020	0.0044
E_4	2.0158	0.2103	0.4659
E_5	0.3563	0.0011	0.0029
E_6	8512.30	740.56	950.78
E_7	17.31	2.61	5.74

VI: CONCLUSION

EDMTRE which considers emissions reduction, health and ecosystems effects has been formulated and solved using *MFA-LF-DM* and SPA. IEEE 30 Bus systems with high Wind and Solar Penetration was applied as the test network. The simulation adopted the *Modified ReCiPe Version 1.3 Model* for the midpoint indicators. From the simulated results, it is apparent that the optimal environmental benefits of RETs are accurately determined with resource cost as a constraint. However the adverse effects of solar are four times more than those of wind. That is, with a thermal base of 25.9%, the overall end point impact for wind is 0.55% while that of solar stands at 2.13%. Consideration of other forms of RE in addition to wind and solar will form an area of further research and development. Also the end point indicator on resources cost need to be formulated and investigated. EORECC can be expounded further to include other environmental benefits of RETs. Generally, the tradition that *"RE is free, harmless and clean"* must be technically moderated.

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