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Research article

The hybrid method based on ant colony optimization algorithm in multiple factor analysis of the environmental impact of solar cell technologies

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Abstract: The increasing demand for solar energy drives the mass production of diverse photovoltaic (PV) systems and, consequently, the growth of used solar panels and their environmental footprint. This study applied a new hybrid optimization method based on particle swarm and ant colony optimization algorithms to solve the problems of PV module toxicity. The Weibull distribution function was used to measure the service life of PV modules under a variety of failure scenarios. The simulation results show that PV modules that were guaranteed to have the service life of 25–30 years mostly last 20–25 years. The toxicity coefficient and the use of a hybrid method suggest that the time period when a solar module exhibits a maximum efficiency with a minimal environmental footprint ranges from 15 to 20 years. It was established that this interval corresponds to the level at which the amount of waste does not exceed the amount of energy generated with a minimum number of failures. The proposal will be effective in predicting the performance of solar systems. This approach can be improved in terms of cost and benefit and employed in the future research on renewable energy and ecosystems.

Keywords: Ant Colony Optimization Algorithm; new technologies; Particle Swarm Optimization Algorithm; PV panel waste; solar energy

1. Introduction

Potential for the transition from traditional to renewable energy is annually growing. Solar energy advancements made in the past twenty years reduced the cost of photovoltaic (PV) cells and hence contributed to an intensive growth in demand for renewable energy. The global solar energy capacity increased over 300-fold between 2000 and 2019. New solar technologies promise to improve the efficiency of solar panels and lower costs further. Currently, there are three types of PV panels on the world market (i.e., mono-, polycrystalline, and thin-film) with their own pros and cons [1]. These panel types vary in costs, performance, appearance, material they are made from, lifespan, and environmental footprint [1]. In a joint report on the strategy for the utilization of solar modules, the International Renewable Energy Agency and the International Energy Agency projected that by 2030 the world waste of photovoltaic (accumulated) will amount to 1.7 to 8 million tons, depending on whether it will be regular loss (modules that have worked their lifetime in 25 to 30 years) or early loss (prematurely removed modules, before the expiration of their service life for a number of reasons—replacement of obsolete equipment, mechanical damage to panels, etc.) [2]. By 2050, the volume of waste PV-modules, which served their term, will be 60 to 78 million tons. Given these forecasts, the global community will face the problem of PV-module recycling in the next decade. The existing proposals for sorting and reprocessing used PV panels only partly solve this problem. The bulk of money and time is spent on the diagnostics and replacement of PV panels, which leads to a decrease in productivity and an increase in energy costs. To eliminate these negative consequences, an optimization algorithm is required that is used for predicting the challenge of solar module replacement. The optimal solutions to minimize costs and waste are also needed.

Optimal solutions are determined via methods of direct optimization. One of the most common approaches in nonlinear programming is to seek parameters that satisfy the nonlinear constraints at selected points. This approach shows high reliability at the price of complex method construction and lengthy calculations [3]. This method requires an initial approximation and can converge to a local extremum near the approximation, while generally showing low accuracy [4]. Sequential quadratic programming (SQP) is also among the most common and effective optimization algorithms for solving a sequence of quadratic subproblems [5]. Its disadvantage is that some intermediate iteration points do not satisfy the constrained condition. Among other effective methods is the Particle Swarm Optimization (PSO) algorithm [6], inspired from the behavior of a biological system such as a bird flock or a swarm. The swarm or a combination of particles is set to find the best solution with regard to a given measure of quality. Swarm intelligence methods have greater reliability in finding a global maximum and higher accuracy. The shortcomings are that PSO computation takes a long time to accomplish. The evolutionary computation techniques include genetic algorithms [7]. These algorithms deal with a set of individuals (population) or strings (chromosomes) that represent single solutions to the problem. While genetic methods generate multiple solutions, other optimization algorithms mostly operate with only one solution, improving it. In turn, genetic algorithms belong to the class of inaccurate approximation methods of soft computing. The Ant Colony Optimization (ACO) algorithm [8] is based on the above methods, eliminating their shortcomings. ACO is one of the most effective algorithms to solve many complex optimization problems such as the Traveling Salesman Problem, the Quadratic Assignment Problem, the Job-Shop Scheduling Problem, and so on [9]. For example, ACO was applied to the vehicle routing problem to minimize the number of vehicle routes required to deliver products between depots and customers while minimizing the vehicle travel time or distance [10,11]. Another type of problems that have been solved using the ACO approach is the facility location problem. The objective is set to find a subset of alternative facility locations that minimize the combined fixed cost of facilities and the variable cost of delivering products from the selected facilities to the customer locations [12]. A hybrid ACO approach employed for cancer detection in computed lung tomography has yielded results that were highly accurate [13]. Hence, ACO found its application in various fields of science, becoming a universal method. In this study, ACO was applied to a specific problem for probabilistically generating a solution with regard to changes in weather conditions, object appearance, and etc.

This article proposes a hybrid optimization algorithm based on ACO and PSO to forecast a decrease in PV energy efficiency and the growth of PV waste. The computational data may be used in solar upgrade planning and to employ technologies that are more efficient.

2. Materials and methods

The hybrid optimization framework combines ACO and PSO algorithms.

2.1. Ant Colony Optimization

ACO is a metaheuristic approach for solving complex combinatorial optimization problems, inspired by the behavior of ant colonies in finding the shortest path from food sources to their nests. To increase efficiency and efficacy of the colony, artificial ants are given certain capabilities: living in an environment where time is discrete; having an internal memory of the ants' previous actions; and pheromone deposition. The amount of pheromone laid on paths of ant travel should be proportional to the quality of the resultant solution. In ACO system, a colony with a finite number of ants concurrently and asynchronously moves through adjacent states of the problem, applying a stochastic transition policy that considers two parameters called *trail intensity* and *visibility*. Trace intensity refers to the amount of pheromone in a path, which provides information about the priority of a given path. Visibility indicates a priori desirability of the move such as cost or distance. Therefore, moving through adjacent steps, ants incrementally build a feasible solution to the optimization problem. Once an ant has found a solution, it evaluates the solution and deposits pheromone on the connections it used in various ways: without waiting for the end of the solution (step by step pheromone update) and by retracing the same path backwards and updating the pheromone trail (delayed pheromone update) [9].

For a complex optimization problem to be solved, one first has to derive a finite set of solution components $\mathcal{C}$, which are used to compile solutions to the problem. Second, one has to define a set of pheromone values $\mathcal{T}$, which represents a set of pheromone values $\tau_i \in T$ typically associated to solution components. The pheromone model is used to probabilistically generate solutions to the problem under consideration by generating them from the set of solution components. In general, the ACO approach attempts to solve an optimization problem in the following two steps: (1) candidate solutions are constructed using a pheromone model, that is, a parameterized probability distribution over the solution space; (2) candidate solutions are used to modify the pheromone values in a way that is deemed to bias future sampling toward high quality solutions. The pheromone update aims to concentrate the search in areas of the search space that contains high-quality solutions.

The finite set of solution components $\mathcal{C} = \{\mathrm{c}1, \dots, cn\}$ is derived from the discrete optimization problem under consideration. Each solution construction starts with an empty sequence. Then, the current sequence s is at each construction step extended by adding a feasible solution component from the set $\mathcal{N}(s) \subseteq \mathcal{C} \backslash s$. The specification $\mathcal{N}(s)$ depends on the solution construction mechanism. The choice of a solution component from $\mathcal{N}(s)$ is at each construction step performed probabilistically with respect to the pheromone model. In most ACO algorithms, the transition probabilities are defined as:

$$p(c_i|s) = \frac{[\tau_i]^{\alpha} \cdot [\eta(c_i)]^{\beta}}{\sum_{c_j \in \mathcal{N}(s)} [\tau_j]^{\alpha} \cdot [\eta(c_j)]^{\beta}}, \forall c_i \in \mathcal{N}(s) \tag{1}$$

Where: η represents an optional weighting function, that is, a function that, sometimes depending on the current sequence, assigns at each construction step a heuristic value $\eta(c_j)$ to each feasible solution component $c_j \in \mathcal{N}(s)$.

The values that are given by the weighting function are commonly called the heuristic information. Furthermore, the exponents α and β are positive parameters whose values determine the relation between pheromone information and heuristic information.

ACO will differ in the update of the pheromone values they apply. This calls for the outline of a general pheromone update rule. First, a pheromone evaporation, which uniformly decreases all the pheromone values, is considered. Second, one or more solutions from the current and/or from earlier iterations are used to increase the values of pheromone trail parameters on solution components that are part of these solutions:

$$\tau_i \leftarrow (1-\rho) \cdot \tau_i + \rho \cdot \sum_{\{s \in S_{upd} | c_i \in s\}} w_s \cdot F(s) \tag{2}$$

for *i=1. , , n*. Hereby, *Supd* represents the set of solutions that are used for the update; $\rho \in (0,1)$ represents the evaporation rate, and $F: S \mapsto \mathbb{R}^+$ is a quality function such that $f(s) < f(s') \Longrightarrow F(s) \geq F'(s'), \forall s \neq s' \in S$.

In other words, if the objective function value of a solution *s* is better than the objective function value of a solution *s'*, the quality of solution *s* will be at least as high as the quality of solution *s'*. The equation below allows an additional weighting of the quality function, i.e., $w_s \in \mathbb{R}^+$ and denotes the weight of a solution *s*. Exemplifications of this update rule are obtained by different specifications of *Supd* and by different weight settings.

In many cases, *Supd* is composed of some of the solutions generated in the corresponding iteration (hereafter denoted by S_{iter}) and the best solution found since the start of the algorithm (hereafter denoted by s_{bs}). Solution s_{bs} is often called the best-so-far solution. An example of a pheromone update rule that is more used in practice is the IB-update rule, where IB stands for best iteration-best. The IB-update rule is expressed as follows:

$$S_{upd} \leftarrow \{s_{ib} = argmax\{F(s) | s \in S_{iter}\}\}, w_{s_{ib}} = 1, \tag{3}$$

that is, by choosing only the best solution generated in the respective iteration for updating the pheromone values.

2.2. Particle Swarm Optimization

PSO technique is based on a swarm behavior [14]. This method can be used to solve many problems including for finding a minimum value in a function. PSO belongs to the class of evolutionary algorithms and does not need a gradient to be calculated, enabling optimization problem-solving in cases where the calculation of the gradient is difficult to not possible to achieve.

The PSO algorithm maintains a population of particles *s* or a swarm, where each particle represents a candidate solution to the optimization problem. Each i-th particle can be represented as an object with a number of parameters: particle position x_i; particle velocity v_i; and the personal best particle position y_i. The particle's personal best position refers to the position at which the personal best value has been found. Assume f as a function that needs to be minimized. In this case, the best personal position at a certain time step will be given by:

$$y_i(t+1) = \begin{cases} y_i(t) \; if \; f(x_i(t+1) \geq \; f(y_i(t)) \\ x_i(t+1) \; if \; f(x_i(t+1) < \; f(y_i(t)) \end{cases} \tag{4}$$

There are two versions of the PSO algorithm, *gBest* and *pBest*. In Personal Best PSO, personal best is the best solution a particle has found so far. Each particle knows its best value (*pBest*) and its position, which constitute a personal experience of each particle. Furthermore, each particle knows the best value in the group (*gBest*) among *pBests*. This information gives insights into the performance of other particles. The global best position at a certain time step is calculated by:

$$\hat{y} \in \{y_0(t), y_1(t) \dots y_s(t)\} | f(\hat{y}(t)) = min\{f(y_0(t)), f(y_1(t)) \dots f(y_s(t))\} \tag{5}$$

The above equation states that $\hat{y}$ is the best position discovered by any of the particles so far.

The stochastic component of the particle movement is represented by two random parameters, $r_1 \sim U(0.1) \quad and \quad r_2 \sim U(0.1)$, which are scaled by means of constant acceleration coefficients c_1 and c_2. The constant acceleration coefficients regulate the step size of a particle in an iteration of time. Normally, $c_1, c_2 \in (0.2)$. The velocity of particle i is calculated separately in each dimension $j \in 1 \dots n$ so that the particle's velocity at next time step $t+1$ is calculated by the formula:

$$v_{ij}(t+1) = w_c v_{ij}(t) + c_1 r_1(t)[y_{ij}(t) - x_{ij}(t)] + c_2 r_2(t)[\hat{y}(t) - x_{ij}(t)] \tag{6}$$

Hereby, c2 regulates the association between the global best position and the velocity of any particle, and c1 regularizes the association of the personal best position of the particle and its velocity. To improve the convergent behavior of the algorithm, the inertia coefficient w_c is introduced [15]. Particle's position is updated by the formula:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{7}$$

Once the above steps are completed, one has to calculate the value of a target function at each new point to determine if any particle moved to its best position. Among all new positions, the algorithm seeks a global best and a relative value of the function.

2.3. Multi-dimensional space plotting

To evaluate and compare the effectiveness of a given algorithm, the function was visualized as a multi-dimensional plane. For a function of two variables *z=f (x, y)*, a surface is viewed in a three-dimensional space with coordinates x, y, z. The problem *f (x, y) → min* refers to the identification of the lowest point on a three-dimensional surface. To represent a three-dimensional surface, the contour lines are used, also known as the curves of intersection of the planes z=const with the surface *f (x, y)*

[16]. Hereby, the representation of the function is unordered, with many maxima and minima. Subsequently, the problem is reduced to finding the optimal solutions (maxima and minima) of the function through a metaheuristic algorithm.

2.4. Experimental data gathering procedure

This work assessed a variety of popular PV modules from various manufacturers (e.g., Canadian Solar, Sunpower, LG, Hyundai, SolarWorld, Hanwha, Kyocera, Hyundai, Trina, etc.) in terms of waste performance. The technical specifications (i.e., the nominal power, weight, and maximum efficiency) of these PV modules are given in Table 1.

Table 1. The global PV module offerings and their technical specifications.

PV module	Average nominal power, W , W/m^2	Average weight of 1 m^2, P, kg/ m^2	Efficiency, %
c-Si	200	15.75	17.5–26.7
poly-Si	170	13.92	13–20
a-Si	56	8.2	5–12
CdTe	90	16.7	16–22.1
CIGS	111	17.5	16.2–22.9

A total of 100 PV modules from different types that were available on the Internet (eBay, Amazon, Alibababa, etc.) were selected to assess the amount of waste generated at the end-of-life stage or failure.

To analyze service life of modules, the Weibull distribution function was employed [17,18], which is comprised of two parameters: shape (α) and lifetime (T). The probability density function $f(t)$ is expressed as follows:

$$f(t) = \frac{\alpha}{T}\left(\frac{t}{T}\right)^{\alpha-1} e^{-(t/T)^{\alpha}} \tag{8}$$

According to (8), the lifetime of the module depends on the Shape Parameter, which affects the frequency of failures in operation over time [19]. If the value of $\alpha < 1$, the failure rate will decrease over time. The presence of minor flaws in module design or material results in a relatively low probability of failure during the early years of service, which then decreases gradually. The value of $\alpha = 1$ indicates a constant failure rate, that is, failures may occur randomly during the warranty period. When $\alpha > 1$, the failure rate will increase over time, indicating the presence of premature wear issues. The Time Parameter is defined as the time during which 63.2% of PV modules will have failed. Here, two time parameters have been chosen that correspond to the average lifespan of PV systems. Furthermore, the following values of α were chosen (Table 2) that have been obtained empirically in previous studies [20–23].

Table 2. PV module degradation scenarios defined as a function $f(t)$ (1).

T, years	α Early-loss	Regular-loss	upper
25 30	3.5	5.36	7

Figure 1 shows an example of a failure probability density plot.

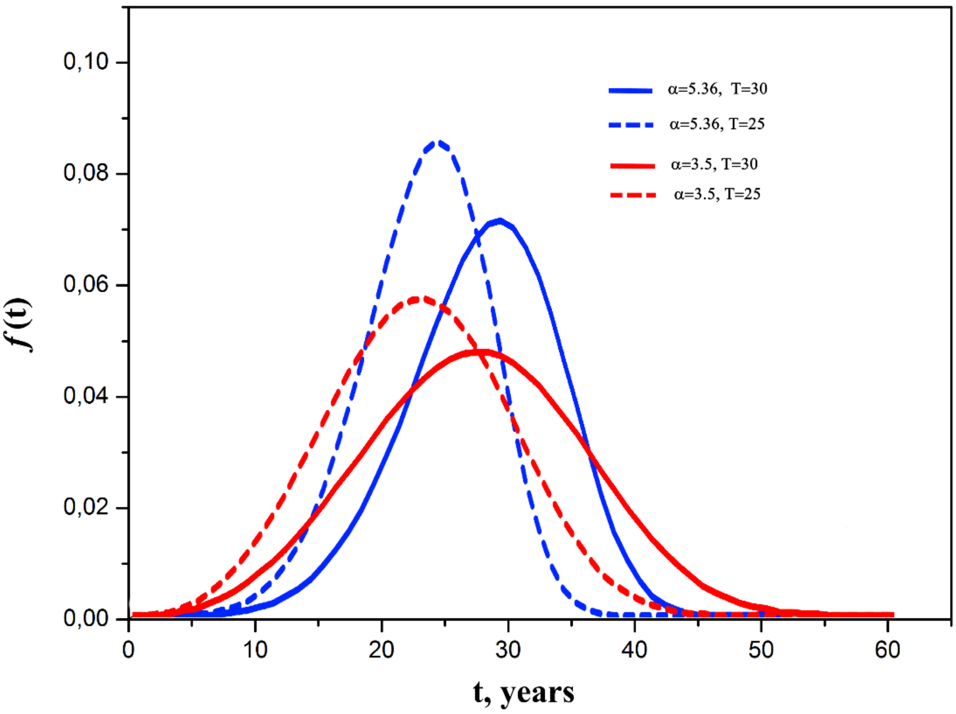

Figure 1. A graph showing the probability density *f(t)* of PV module failure for certain values of α and T.

The probability density function *f(t)* defines the unreliability function, which is the probability of failure in the time period (0; τ), and is expressed as follows:

$$F(t) = \int_0^{\tau} f(t)dt = 1 - e^{-(\tau/T)^{\alpha}} \tag{9}$$

This work took data in Table 2 and equations (8) - (9) to generate 6 scenarios with different failure probabilities, which then will be used to assess the PV module waste performance. The ratio of produced waste to installed PV capacity per year is expressed by the toxicity coefficient (*Kt*), which is defined as:

$$Kt = \frac{\mathrm{P}}{W_p} WF(t) \tag{10}$$

Where: P – waste, W – installed PV capacity.

The toxicity coefficient was found for all samples and failure scenarios for the period 2000-2050. The accumulative capacity Wp was 100 MW. The landscape of the function was constructed by using coordinates of dependence on time *t* and efficiency *E*.

2.5. Hybrid optimization method

A hybrid algorithm for optimizing PV toxicity consists of two components, PSO and ACO. It implies that the following steps should be performed:

1) feed data obtained through (10).

2) apply the PSO algorithm to find all minima and maxima of the function, in which, according to equations (4)–(7), the values are run through two cycles with opposite conditions.

3) identify the search interval.

4) employ the ACO algorithm to find all possible and shortest paths between minima, bypassing maxima. Figure 2 shows a random path from the left edge of the surface to the right edge of the surface in accordance with the rule (3).

5) define the minimum depth by the pheromone trail in the ACO algorithm so that the algorithm could search for prominent minima. The update is performed by using the formula (2).

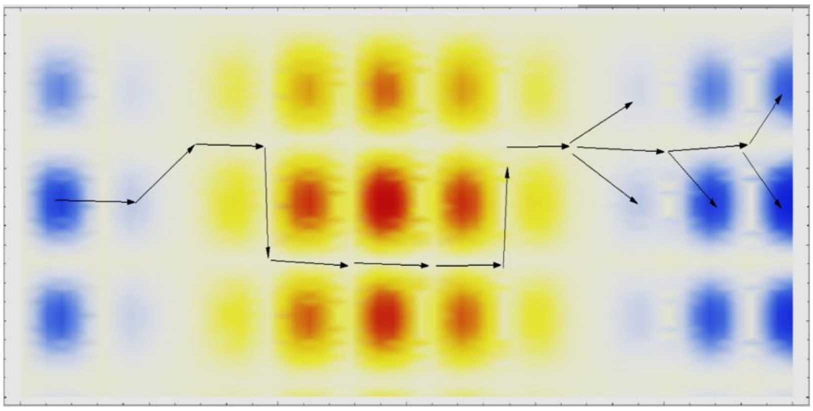

Figure 2. Ants found a random path to minima (blue color) bypassing maxima (red color).

After optimization, the surface representation will contain the best and most probable solutions for *Kt (t, E)*.

3. Results and discussion

Figure 3 shows a 3D image depicting a time-toxicity dependence of different PV modules. As it turns, the PV waste level trend is heterogeneous in nature. The first wave of growth in PV waste took place after the failure of the first generation of PV modules in the early 20s and was not critical. The peak levels of PV module toxicity ($Kt \sim 10^{20}$ kg) refer to the intervals 2030–2040 and 2048–2055, assuming a negative environmental impact of solar panels during these periods. Solar panels with low efficiency (below 16%) are two orders of magnitude less toxic ($Kt \sim 10^{10}$ kg) compared to PV modules with the efficiency of ≥20%. Solar panels that are most commonly used such as monocrystalline silicon (c-Si) and cadmium-telluride (CdTe) solar panels are projected to reach the maximum toxicity (red peaks).

However, this approach is only suitable for probabilistically analyzing the time to a negative impact such as increased PV waste and increased disposal costs. This method does not provide a clear solution for minimizing the environmental footprint of popular solar energy generators without reducing their efficiency. The hybrid algorithm was designed to find all highest and lowest levels of toxicity possible and to find the shortest path to minimum toxicity ($Kt \sim 0.5 \times 10^{10}$ kg). The optimization results are presented as a surface plot in Figure 4. A critical toxicity coefficient was regarded as the averaged toxicity value ($Kt = 2 \times 10^{20}$ kg).

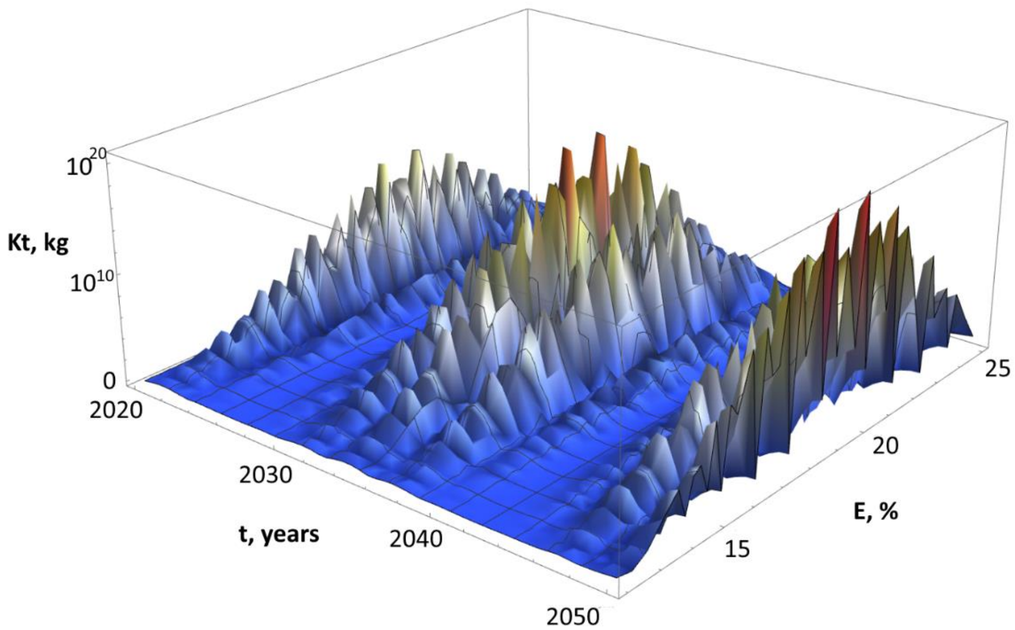

Figure 3. A 2020–2050 toxicity (Kt) forecast for PV modules of different efficiency E and a lifespan of 25 and 30 years.

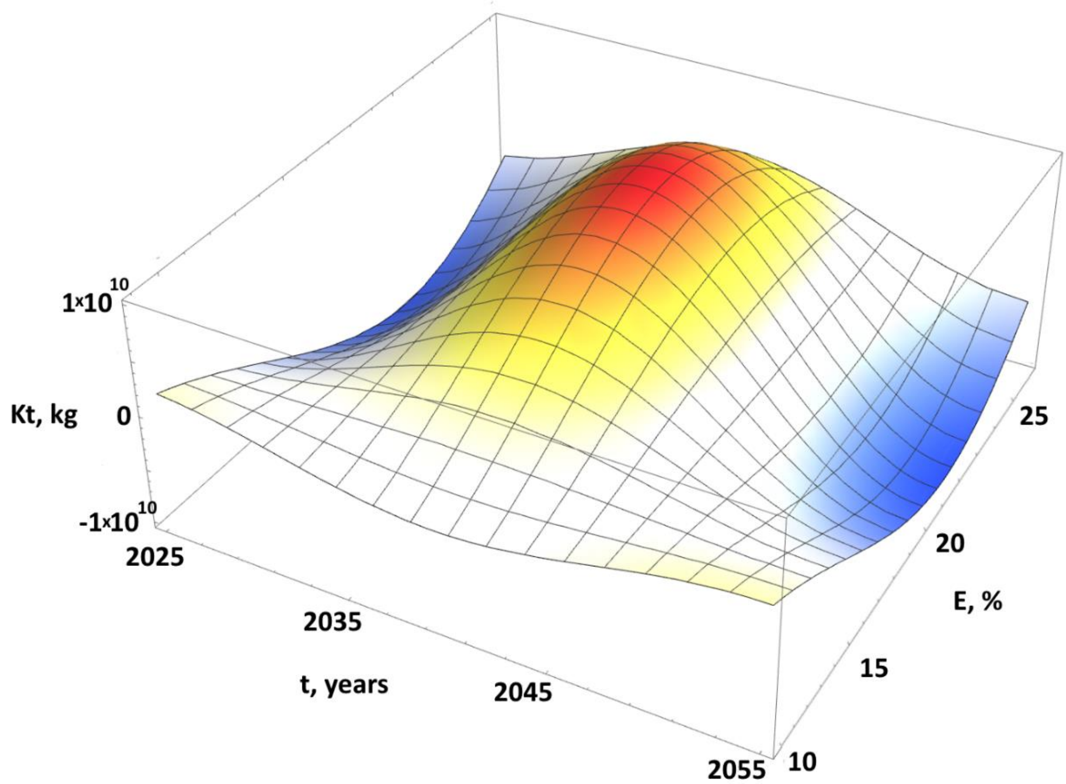

Figure 4. Relative toxicity coefficients of PV modules Kt(t) of different efficiency E and a lifespan of 25 and 30 years after optimization.

According to data obtained, solar modules with higher efficiency ranging from 16 to 20%, c-Si and CdTe modules specifically, are currently less toxic (Kt is equal to -2 × 10^{10} kg) because they were put into service a short time ago. By 2035, their toxicity levels will hit their maxima (Kt ~ 2 × 10^{10} kg), followed by a decline of the two orders of magnitude until 2045.

Let us consider the time-toxicity dependence of Si and CdTe PV modules with efficiency of 16 to 20%. To avoid the maximum toxicity, it is necessary to determine the critical period of toxicity (Kt = 0). Hereby, it is between 2030 and 2040. Consequently, the amount of waste will not exceed the amount of energy generated until 2030. Hence, the revenue will be more than disposal and reinstallation costs. To maintain PV module toxicity at the acceptable level, it is necessary to utilize (recycle) a certain amount of solar panels per year without waiting for them to reach the end of their lifetime. The number of solar panels to be replaced is defined by the type of the panel. For example, solar panels with a 30-year lifetime shall be replaced after 20–25 years of service [20]. A forecast based on Life Cycle Assessment (LCA) projected an increase of waste from c-Si PV panels by 4–14% in 2030 from 43.500 tonnes in 2016 and by more than 80% in 2050 to10.5 million tonnes [24]. The present optimization strategy provides for the most positive forecasts, indicating the acceptable level of relative toxicity. According to the LCA-based assessments of the environmental impact of Si and CdTe PV panels [25], the recycling process must begin before decommission. It was found that the energy payback time for silicon solar panels is 2.6 years, which can be reduced to 1.6 years with the recycling process. For CdTe PV panels, it is about 1.30 years because the cost of their production is lower compared that of Si PV panels. With recycling, these two values become very similar. A screening-level risk assessment of non-carcinogenic and carcinogenic risks associated with cadmium exposure from CdTe PV panel disposal in landfills was performed with a Delisting Risk Assessment Software (DRAS) [26]. The results revealed that health risks associated with disposing used panels in landfills are currently remote. However, the growth of panel disposal rate over time will lead to greater carcinogenic risks. Hence, the choice to landfill or recycle PV panels should be based on a careful analysis of the comparative risks and benefits associated with each option. This approach is estimative, requires a constant information update, and does not yield an approximate solution to the problem of CdTe-PV waste disposal. It was found that with new technologies for saving materials and PV panel efficiency improvement, the use of both materials per unit capacity and potentially hazardous substances reduces [27]. The industry will face new challenges in a renewable energy scenario where resource efficiency, innovations to reduce waste flow, and follow-up initiatives provide opportunities to facilitate a transition to sustainable and economically viable future. The growth of PV module production means an increase of waste recycling and hence the reduction of landfills in a circular production. The global installed PV capacity is expected to increase to 1600 GW by 2030, so the volume of decommissioned PV panels will also increase. Raw materials can be treated and recycled at a rate of 65 to 70% by mass. This estimate is based on expected PV cell technology ratios and related waste composition multiplied by the cumulative waste volume of at least 1.7 million tons by 2030. This estimate is consistent with the present study. In order to regulate circular production, it is necessary to establish a critical volume of waste per year, which is undesirable to exceed, as in the case of critical PV module toxicity coefficient. In addition, the high efficiency of a hybrid optimization algorithm shows good agreement with the study on assessing the potential of various PVs [28]. The authors of that study revealed that metaheuristic and hybrid metaheuristic optimization algorithms were more reliable and showed the best solutions for real power losses, cost and voltage stability index in a power system. Furthermore, the bee-inspired algorithms demonstrated high efficiency in optimizing the cost of investment in renewable energy projects [29,30]. The obtained solutions allow saving on PV panel installation given the geographical position and potential of the panel. The use of a hybrid algorithm to find optimal solutions revealed results that were fairly accurate, which is promising and relevant in terms of solar energy market development and ecology.

4. Conclusion

This work is a first attempt to develop a hybrid method for determining the optimal level of PV toxicity in currently used PV modules throughout their lifetime. The hybrid method in point combines Particle Swarm Optimization and Ant Colony Optimization. The Weibull distribution revealed that in various scenarios, PV modules with a warranted life of 25 to 30 years reached their maximum toxicity levels after 20-25 years of performance. The results of the PSO-ACO algorithm show that the amount of waste will not exceed the amount of energy generated at a toxicity level of $\sim 10^{10}$ kg per year, 15-20 years after the module has been installed. It was found that in order to maintain PV module toxicity at the acceptable level, it is necessary to utilize a certain amount of solar panels per year without waiting for them to reach the end of their lifetime. This approach helps regulate PV module efficiency and disposal (recycling). It thus may be used to predict the potential of the solar systems to yield with less waste and without a sharp loss of capacity. The approach can be improved in terms of cost and benefit in the future.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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