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Selection of abandoned areas for implantation of solar energy projects using Artificial Neural Networks

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Abstract. The increasing demand for energy has intensified recently, requiring alternative sources to fossil fuels, which have become economically and environmentally unfeasible. On the other hand, the increasing land occupation in recent centuries is a growing problem, demanding greater efficiency, particularly in the reuse of abandoned areas, which has become an alternative. An interesting alternative would be installing energy facilities like solar, wind, biomass, and geothermal, in these areas. So, in this way, the aim of this work is to classify these abandoned areas to verify which ones would be suitable for solar energy facilities specifically, to reuse those areas. Artificial Neural Networks (ANNs) trained with the Levenberg-Marquardt Algorithm (LMA) were used for the classification task. The main innovation of this work is the optimization of the initial weights of the ANN using the Quantum-behaved Particle Swarm Optimization (QPSO) metaheuristic, through QPSO-LMA proposed algorithm. In terms of Mean Squared Error (MSE), the QPSO-LMA approach achieved a decrease of 19.6% in relation to the classical LMA training with random initial weights. Moreover, the model's accuracy showed an increase of 7.3% for the QPSO-LMA over the LMA. To validate this new approach, it was also tested on six different datasets available in the UCI Machine Learning Repository and seven classical techniques established in the literature. For the problem of installing photovoltaic plants in abandoned areas, the knowledge acquired with the solar dataset can be extrapolated to other regions.

Keywords: Solar Energy, Soil Reuse, Artificial Neural Networks, Quantum-behaved Particle Swarm Optimization.

1 Introduction

The growing demand for energy has intensified in recent decades, requiring alternative sources to fossil fuels [1], which have become economically and environmentally unfeasible [2–4]. In addition, the increasing occupation of urban spaces in recent centuries has become a problem [5], requiring greater efficiency in land occupation, especially in the reuse of abandoned areas, one of the major current challenges [6].

This problem is more serious when these areas are large and contaminated, constituting a risk to the environment, health and the economy [6,7]. Therefore, renewable energies, such as solar energy, have proved to be feasible alternatives that enable productivity and social and environmental wellness [8]. They are abundant, clean and, above all, free [9,10], and can be used in energy generation projects in areas that are currently unused, reconciling the demand for energy and the recovery of these areas.

These abandoned areas, contaminated by substances harmful to the environment and human health, have attracted the attention of governments and non-governmental organizations [11,12]. Examples can be cited, such as: abandoned mines, generally contaminated by heavy metals [13]; brownfields, which are abandoned industrial installations; areas of the Superfund, an American federal government program for locating and cleaning up contaminated areas; landfills, mainly for the disposal of food leftovers and packaging [14]; and areas for solid waste, as defined by the Resource Conservation and Recovery Act (RCRA).

Today, around the world, there is installed power of approximately 2,180 GW. Together, all the 81,533 points analyzed in this work have an estimated potential of more than 6,775 GW, approximately 3 times what is generated worldwide. This potential is equivalent to over 44,000,000 tons of carbon dioxide (CO₂) that would no longer be released into the atmosphere. There are over ten million jobs in the renewable energy sector. With the creation of renewable projects in areas that are currently out of use, it would be possible to multiply this number, making a positive impact on the environment, the economy and society.

The objective of this paper is to develop a classification methodology, based on Artificial Intelligence (AI) and Quantum Theory (QT), to automatically carry out the classification of abandoned areas suitable for the settlement of these power plants. This innovation will be tested using the classification problem of abandoned areas suitable for solar energy facilities as well as another six classic problems from the literature. The results will also be compared with seven classification algorithms established in the literature.

The main contributions of this article are:

- Improvement of Artificial Neural Network (ANN) performance by optimizing initial weights using the Quantum-behaved Particle Swarm Optimization (QPSO);
- Automatic selection of suitable areas for the implementation of renewable energy projects.

This paper is organized as follows. Section 2 presents the theoretical framework. The methodology for the proposed problem is presented in Section 3. Section 4 shows the results and a discussion about them for the set of solar data; besides, this section shows six datasets from the literature and other seven classical algorithms used for comparison and validation of the proposal. Finally, the conclusions are presented in Section 5.

2 Theoretical Framework

Traditional AI aims to represent intelligent behaviors through exact and complete representations of knowledge. However, many real-world problems cannot be described exactly, or the appropriate knowledge of their operation is not available (they are “black boxes”). Computational Intelligence (CI) emerged as a solution to these difficulties, without requiring much a priori knowledge of a problem, producing robust and adaptable (flexible) solutions for diverse scenarios [15].

The field of CI involves paradigms of Computational Science and Operational Research with a view to implementing systems that represent intelligent behavior (which may be defined as the ability to learn and apply this learning to new scenarios) in complex decision-making processes. Of these paradigms, those inspired by nature are predominant, such as ANN, Fuzzy Systems (FS) and Evolutionary Computation (EC), in addition to hybrid systems, which have advantages such as flaw tolerance and incompleteness or inaccuracy of the data used as an input for the algorithms [16].

One type of problem addressed by the CI is the pattern classification problem, such as text recognition [17,18], image recognition [19], classification of bone fractures [20,21], endometriosis [22], arrhythmia [23,24], mineral quality [25] and the identification of medicinal herbs [26].

Among the many techniques available to address classification problems, we may cite Naïve Bayes [17,27], Decision Trees [28,29], Support Vector Machines [29,30], Gaussian Process Classification [31,32], k-Nearest Neighbors [33–35], Ensemble methods [36–38] and Neural Networks [39–41].

With the rapid advances in the field of AI in recent years, many approaches have been implemented to improve ANNs. To achieve a general overview of the field, scientific articles were collected from the Scopus, Science Direct and Web of Science databases, which were searched using the terms “computational intelligence”, “artificial neural network”, “hybrid optimization” and “machine learning”.

Analyzing the most cited articles published between 2019 and 2020, hybrid models use metaheuristics in two main ways. First, for the optimization of the ANN hyperparameters, such as the number of hidden layers, the number of neurons in each hidden layer and the damping factor (in the case of the Levenberg-Marquardt Algorithm, LMA) or learning rate and momentum (for the Gradient Descent Algorithm, GDA). Second, metaheuristics, mainly evolutionary strategies, are used to replace traditional optimization methods, such as the LMA. Our proposal is to use the qualities of both algorithms (QPSO in the initialization of synaptic weights and LMA in the training phase) to improve the performance of the ANN to classify abandoned areas suitable for solar energy facilities to reuse them based on the solar dataset obtained from the website of the United States EPAs, as explained ahead at section 3.1.

2.1 Quantum-behaved Particle Swarm Optimization

In the quantum version of the PSO algorithm, the state of the particle is given by a wavefunction $\psi(x, t)$, instead of its trajectory (velocity and position). In the quantum realm, the term trajectory is meaningless because of the uncertainty principle [42]. The

probability that a particle is in each position can be calculated from its probability density distribution $|\psi(x, t)|^2$.

Employing the Monte Carlo method [43], the particles update its position according to Eq. (1):

$$\begin{cases} X_{i+1} = p + \beta \cdot |Mbest_i - X_i| \cdot \ln\left(\frac{1}{u}\right), & \text{if } k \geq 0.5 \\ X_{i+1} = p - \beta \cdot |Mbest_i - X_i| \cdot \ln\left(\frac{1}{u}\right), & \text{if } k < 0.5 \end{cases} \quad (1)$$

where β is the contraction-expansion coefficient [44], u and k are random numbers in the range $[0,1]$, generated from a uniform distribution. The global mean best ($Mbest$) of the population is defined as the mean of the $pbest$ positions of the swarm.

The contraction-expansion coefficient β is the only parameter to be tuned in the QPSO algorithm, and this can be done through Bayesian optimization [45]. The local attractor to guarantee convergence of the QPSO algorithm [44,46] is defined by Eq. (2).

$$p = \frac{\varphi_1 \cdot pbest + \varphi_2 \cdot gbest}{\varphi_1 + \varphi_2} \quad (2)$$

φ_1 and φ_2 are random numbers generated from a uniform distribution in the range $[0,1]$. Alternatively, this numbers can be generated from a positive Gaussian distribution with zero mean and unit variance, which leads to a large number of small amplitudes in the movement of the particles [46].

QPSO algorithm is proven to be more effective than other implementations of evolutionary algorithms in most scenarios [43,47–50].

3 Methodology

In this section, the methodology used in the work is presented, along with the QPSO approach used for ANN initialization (Figure 1).

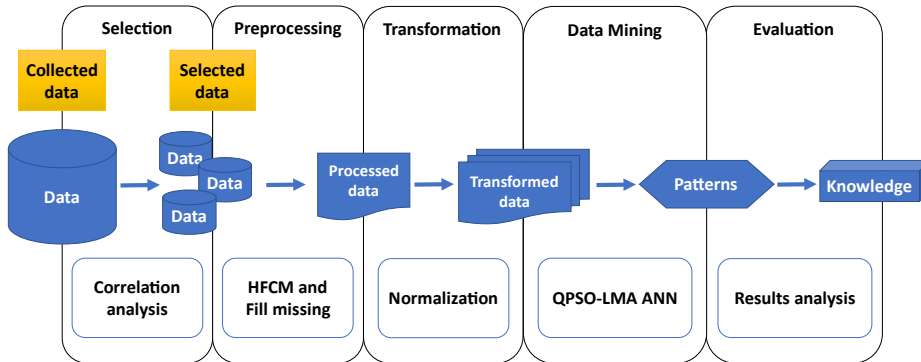


Fig. 1. Methodology phases. Source: the authors.

The methodology was proposed in five main stages: data selection, pre-processing, transformation, data mining and evaluation of the results. In the selection stage, the data were collected from government databases and selected for use in the proposed algorithm. The pre-processing involved filling in missing and removing correlated variables. In the third stage, transformation, the data was normalized to be used as input to the ANN. The data mining stage represents the execution of the algorithms and, finally, the results were analyzed.

3.1 Data Collection and Pre-processing

The solar dataset used in the problem was obtained from the website of the United States Environmental Protection Agency (EPA). The agency oversees the RE-Powering America's Land initiative, which identifies abandoned areas with a potential for recovery and the implementation of renewable energy projects.

With the RE-Powering Mapper tool, it is possible to visualize and download information on renewable energy potential in contaminated lands. Using screening criteria developed in collaboration with the National Renewable Energy Laboratory (NREL) and other state agencies, the EPA has pre-screened over 81,000 sites (at the time of this research) for their renewable energy potential.

The raw data totals 81,533 instances, each of which has 13 independent variables, in addition to 3 dependent variables. The dependent variables have to do with the potential of the location for photovoltaic solar facilities.

Of the 81,533 points analyzed, one or more of the variables were lacking for 32,429 data points, which needed to be filled. To make up for this deficiency, the average of each variable could be used, which might lead to discrepancies, as the range of the set was significant. With this in mind, it was proposed that the instances could be clustered into smaller sets, using the HFCM algorithm [51], with a view to reducing the scope of each variable in order to perform linear interpolation to supply the missing data.

The new generated data have a lower variance compared to those generated by an interpolation performed for the whole set at once, without the linear interpolation carried out in each cluster. As the Neural Networks demand that all variables have the same dimension in the training and testing phases, it was necessary this stage of data preprocessing.

Compared to the use of a complete data set, without missing data, a deterioration in the results and a consequent loss of accuracy can be assumed. Therefore, this preprocessing phase is important in reducing this deterioration.

It was necessary that no variable, in each instance of any of the clusters, should be left empty. At the same time, the clusters had to be small enough to minimize distortions. Therefore, after many preliminary tests, the number of clusters was experimentally set at 200, with the number of instances per cluster varying from 42 to 1,863, with an average of 407. The clusters that were formed allowed a reduction in the amplitude of each variable, making the interpolation of the missing data more realistic.

After collection and preprocessing, the data were separated into input and target sets for the ANN initialized by the QPSO algorithm, using the holdout strategy, considered one of the most reliable when estimating the accuracy of a predictive model [52]. The

data were divided into two sets, training and test, with 50% of the data in each, randomly selected, with a view to a more secure evaluation of the quality of the classification and greater computational simplicity in relation to the k-fold cross-validation [53–55]. For equivalence, Bayesian Regularization was used in the neural network, which dispenses with the use of the validation set.

3.2 Proposed Algorithm (QPSO-LMA ANN)

The proposed initialization process consists of minimizing the mean squared error (MSE) between the target values of the ANN and the values predicted during the learning process, using the QPSO algorithm, called here by QPSO-LMA ANN, or simply, QPSO-LMA. The set of weights and bias, w , corresponds to the position of the particles to be optimized by the QPSO algorithm (w is initialized as an array of random values).

In the pseudocode shown in Algorithm 1, H is the number of neurons in the hidden layer, N is the swarm size for the QPSO algorithm, D is the dimension of the problem (function of the number of variables in the problem: inputs and targets dimensions, and the number of neurons in the hidden layer), and f is the error function (MSE) that should be minimized.

Input: $input, target, H, iter, N$

Output: $w_{best}, output$

1. $i \leftarrow size(input)$
2. $t \leftarrow size(target)$
3. $D \leftarrow (i + 1) * H + (H + 1) * t$
4. $w \leftarrow random(1, D)$
5. $f \leftarrow MSE(w, input, target)$
6. **while** $\neg StopCondition$
7. $[output, w] \leftarrow QPSO(f, D, N, iter)$
8. **end**
9. $w_{best} \leftarrow w$
10. **Return**($w_{best}, output$)

Alg. 1. QPSO pseudocode for ANN initialization.

As *output*, we will have the values predicted by the network, which will be compared with the *target* values to measure the percentage accuracy, and the optimized weights (w_{best}), which were also used for the initialization of the LMA in a feed-forward ANN, as they have a strong influence on the convergence of the algorithm.

The difference between this methodology and other proposals [56,57] is in the fact that here the metaheuristic was used in the initialization phase of the algorithm, aiming to bypass the trap of local minimums to which the LMA algorithm is subjected in its initial phase [58]. Thus, the algorithm became more effective in the search for the global

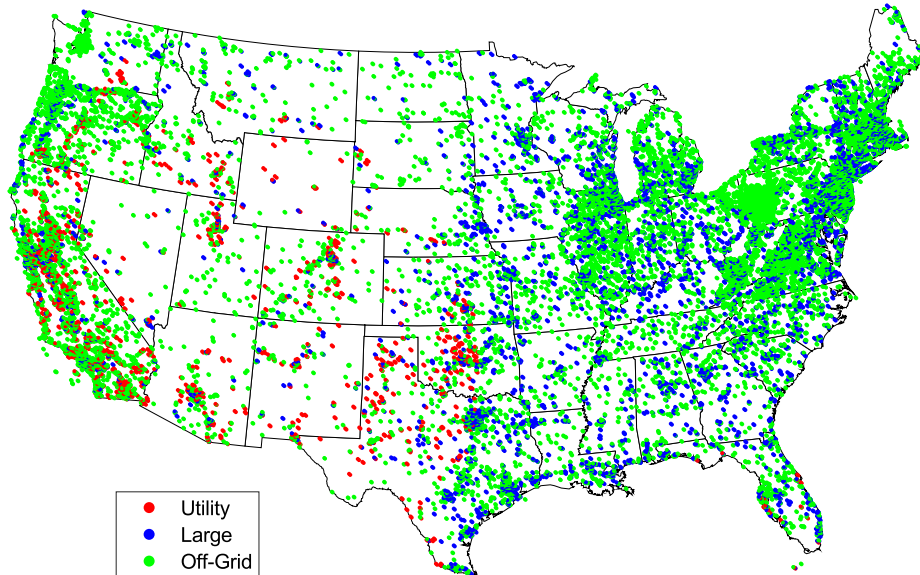
minimum without becoming computationally expensive, as in the proposals presented in the literature.

4 Results and Discussions

In this section the results of the solar dataset are presented, as well as the other six datasets from the scientific literature. The datasets testing is intended to compare the performance of the proposed technique and its validation alongside what has already been developed regarding classification problems. An Intel i7-2600 (3.40GHz) computer was used, with 16GB of RAM. All the algorithms were implemented in MATLAB, version R2018b.

4.1 Solar Energy Dataset

Considering the solar dataset presented at section 3, the QPSO-LMA hybrid technique achieved a decrease in terms of MSE of 19.6% in relation to the classical LMA training with random initial weights. An analysis of the percentage accuracy (see Table 1), for the test set, showed an increase of approximately 7.3% for the QPSO-LMA over the LMA, rising from 75.5% accurate to 81.0%. Figure 2 shows the classification results and the correctly classified locations for the best result obtained by the QPSO-LMA algorithm.



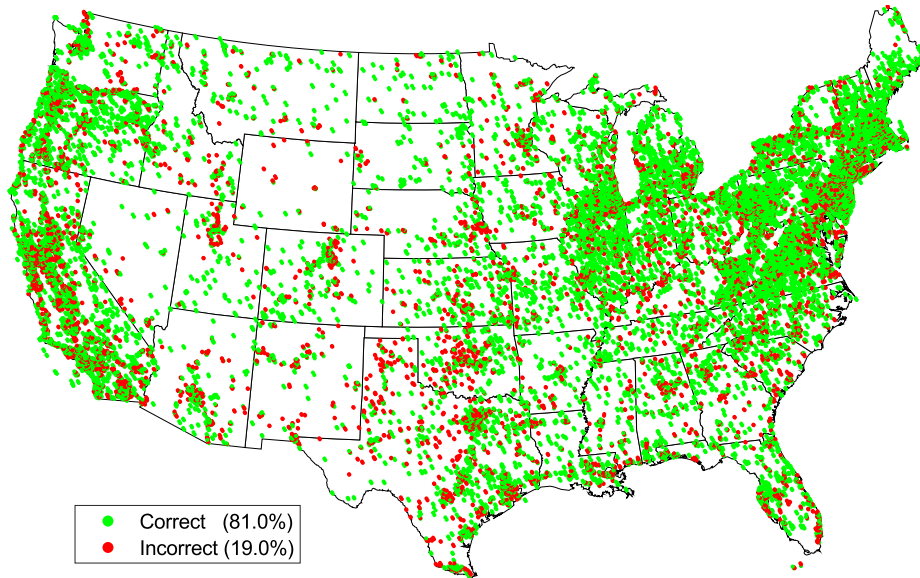


Fig. 2. Classification results (top) and accuracy (bottom) with QPSO-LMA.

The incorrectly classified points are distributed throughout the American territory, as well as each type of abandoned area, leading to the conclusion that there was no prejudice to the classification due to the imbalance of the dataset. The classification accuracy for off-grid, large scale and utility scale are 83.9%, 71.6% and 70.9%, respectively. Errors regarding off-grid areas (class 1) were concentrated in class 2 (large scale) because it has more similar attributes than class 3 (utility scale). The same happened with the other classes.

4.2 Datasets from Literature

The proposed algorithm was also tested on six datasets from the literature, the most cited in the UCI Machine Learning Repository on the date of data collection, to confirm its effectiveness. The results were also compared using some classical algorithms: Linear Discriminant Analysis (LDA), Naive Bayes (NB), Decision Trees (DT), Support Vector Machines (SVM) and Random Forest (RF), an ensemble learning strategy. These techniques have also been tested with Bayesian parameter optimization. Two hybrid techniques from the literature were also tested, which combine metaheuristics and neural networks with parameter optimization [56,57]: Artificial Bee Colony Based Levenberg-Marquardt Algorithm (ABC-LMA) and Accelerated Particle Swarm Optimization Based Levenberg-Marquardt Algorithm (APSO-LMA).

All the best results were obtained with the QPSO-LMA algorithm, achieving the objective of the work of proposing a new and efficient initialization strategy of the weights and bias for ANNs to solve, with maximum accuracy, the classification of abandoned areas problem which could be suitable for solar energy facilities. Table 1 shows the accuracy results for the test dataset with each algorithm. The datasets are: 1

– Solar; 2 – Breast Cancer; 3 – Crab Gender; 4 – Ovarian Cancer; 5 – Thyroid Function; 6 – Parkinson Disease; and 7 – Ionosphere.

Table 1. Results for seven comparative techniques.

	1	2	3	4	5	6	7
LMA	75.5%	90.1%	91.4%	89.9%	90.2%	81.3%	88.3%
QPSO-LMA	81.0%*	93.4%*	93.9%*	94.0%*	93.6%*	84.2%*	89.7%*
LDA	69.7%	84.8%	88.5%	72.9%	90.7%	80.4%	85.1%
NB	61.0%	90.7%	73.3%	90.7%	91.9%	76.2%	86.7%
DT	71.2%	91.7%	87.0%	85.1%	91.4%	79.3%	83.9%
SVM	74.3%	92.2%	91.0%	92.5%	92.1%	83.4%	87.8%
RF	75.5%	90.8%	86.0%	87.8%	92.7%	80.4%	88.1%
ABC-LMA	79.2%	89.4%	90.1%	88.7%	90.3%	79.8%	85.7%
APSO-LMA	78.1%	90.2%	92.0%	90.2%	92.5%	80.8%	88.4%

* indicates the best result for each dataset.

For the solar energy scenario, the increase in accuracy represents a reduction in error, consequently greater efficiency in choosing the best suitable areas for generating renewable electricity. It is worth mentioning that, in the references found in the literature, there is normally no division of data in training and testing, with only the training phase, where the error is significantly smaller.

5 Conclusion

The aim of this work was to classify abandoned areas where solar energy facilities could be installed to reuse those areas (it is also possible to implement similar decision systems for wind, biomass, and geothermal energy, among others). There is enormous energy potential in these abandoned areas, although they are currently neglected. To achieve the classification goal, an ANN was trained with the LMA, in which the initial weights were obtained through the QPSO metaheuristic.

Currently, renovation projects in these areas are poorly prepared, without the use of data analytics in the decision-making process, which leads to mistaken and often inefficient choices [59]. The only criteria used by EPA and NREL to classify abandoned areas are, usually, value ranges with respect to some of the project's variables (estimated capacity, direct normal irradiance, land area and distance to transmission lines).

Using methodologies like the one presented in this work, it is possible to improve this decision process, reducing errors in choosing the most suitable areas, allowing for efficiency gains in the allocation of resources for the implementation of new energy projects. The areas correctly chosen for renovation will provide greater energy

generation and consequently greater return on the investment made, making renewable energies even more competitive.

The results obtained with the solar energy dataset were validated in six of the most cited datasets in the UCI Machine Learning Repository and showed that the proposed strategy was more efficient in all of them. In addition, seven other classification techniques were tested with the seven datasets, with the QPSO-LMA achieving the best result in all cases. This means that QPSO-LMA could improve the accuracy of ANNs, combining the optimization capacity of the QPSO algorithm with the versatility of ANNs in classification problems.

The knowledge acquired by ANNs with the solar dataset can be extrapolated to other regions of the planet, as only technical variables for solar energy were used. This enables the identification of land in locations that do not yet have adequate classification tools. The QPSO-LMA technique could also be used in other classification problems, including other fields of renewable energies, such as wind and geothermal energy and biomass.

Suggestions for future works also include the application of QPSO-LMA algorithm in other databases, since here we had applied just in the seven databases (on solar energy, our problem, and on six datasets from the UCI repository) which, of course, is a limitation of this paper. In the same way, it will be interesting to use other Data Mining techniques, to compare to QPSO-LMA proposed algorithm as well as new metaheuristics in addition to QPSO. The application of dataset balancing algorithms, be they undersampling techniques (removal of instances belonging to the over-represented class), or oversampling (generation of new instances, through clustering and interpolation, relative to the under-represented class) could also be used. Data encoding [60] could also be performed. It will also be possible to test other methods of unrestricted nonlinear optimization as alternatives to the LMA algorithm.

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