Multi-Objective Site Selection for Coal to Nuclear Power Plant Transition

Omer F. Erdem*[1], Majdi I. Radaideh[1]

[1]Department of Nuclear Engineering and Radiological Sciences, University of Michigan, Ann Arbor, Michigan 48109

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ABSTRACT

The sustainability plans and net-zero carbon emission goals increase the demand for the clean energy sources. These targets can be achieved by nuclear energy. The current challenges facing nuclear power plants should be resolved in order to fulfill this purpose. Decreasing the cost of electricity produced by nuclear power plants would help nuclear energy to develop faster and remain competitive. Considering this, one of the improvable aspects of nuclear power plants is their high capital cost. Having a ready power plant site with pre-built infrastructure and auxiliary buildings has the potential to greatly reduce these capital costs. Coal power plant sites are excellent candidates for siting new nuclear power plants. Using these sites for small modular reactor installations could save billions of dollars in capital cost. Therefore, an accurate method of site selection is required for this purpose. There are 265 US coal power plant sites registered in the Idaho National Labs Nuclear Reactor Innovation Center (INL-NRIC), Fastest Path to Zero Initiative (FPTZ), and Siting Tools for Advanced Nuclear Development (STAND) database. Previous research on this database has been done via weighting applied by analysts which could introduce bias. For a more comprehensive search and site evaluation, we propose and apply multi-objective optimization (MOO) techniques on coal plant sites. Dimensionality reduction schemes are also applied on the existing site attributes of the coal power plant locations in the selected database. The best performing locations are reported for each method and technical implications are discussed.

Keywords: Nuclear power plant, site selection, multi-objective, optimization, data analysis

1. INTRODUCTION

Nuclear energy is a plausible source for achieving net-zero carbon emission goals considering its high energy density. It is one of the energy production methods that does not produce any carbon emission during its operation phase, which makes it a clean energy source with respect to CO_2 emissions. But there are other challenges considering the deployment of nuclear energy. One of the main challenges is its high levelized cost. By considering increasing regulatory requirements and increasing capital costs, nuclear energy had the highest levelized cost of electricity in 2023 [1]. Considering this, one of the improvable aspects of nuclear power plants is their high capital cost. Building the necessary infrastructure and auxiliary buildings is one of the most expensive requirements of nuclear energy. One of the proposed solutions is the reusage of coal power plant sites for nuclear power plant projects. By repurposing the coal facility's infrastructure while replacing a large coal plant with a 1,200 MWe generation capacity, nuclear technology could reduce its capital costs over long term by 15% to 35% when compared to a greenfield construction project, depending on the nuclear technology option and size [2]. When the total costs of nuclear power plant projects are considered, replacing coal power plants with nuclear power plants could save billions of dollars' worth of construction costs. US Department of Energy reports that there are 157 inactive and 237 active candidate coal power plant locations suitable for nuclear power plant housing [2]. Each of these locations has advantages and disadvantages. Since nuclear power plants require long term planning, a very detailed and reliable analysis is necessary for replacing these coal power plants with nuclear power plants.

* Corresponding Author: oferdem@umich.edu

Previous nuclear power plant location selection studies were done by applying weights to existing data. The attributes used for selection change depending on the study. However, all of these methods apply some weight justified by the analyst, in order to form an objective function. The most important attributes these weighting studies use are the geographical features such as fault lines, seismicity, existence of cooling water, and distance to the population centers, national borders, transport infrastructure [3]. Other studies try to simplify this selection by choosing the most relevant attributes from these datasets. These most important attributes can be summarized as seismic activity, population density, cooling water cost, reactor unit cost and consumer proximity [4]. More complex methods use all the available data. Different kinds of data are shared among the subroutines to process them and report to the user via a framework. The more complex nuclear power plant location selection frameworks are able to process financial factors, site factors, welfare factors and project life-cycle factors separately, each of these factors requires weights to analyze them together [5]. But these methods also depend on the user to analyze their weight judgements. These selections are subjective to the analyst who sets the weights, selects the thresholds and preprocesses the data.

In the literature, there are different optimization methods for minimization and maximization problems. These can be grouped as first order algorithms, second order algorithms, stochastic algorithms and genetic algorithms [6]. These methods can perform without any constraint about the input space dimensions, but they accept one fitness function. The data of coal power plant locations have multiple output features. MOO methods are required in the problems with multiple output dimensions. There are classical algorithms and multi-objective genetic algorithms designed for MOO. Some of the classical algorithms are Weighted Sum Method, ϵ-Constraint Method and Weighted Metric Method. Multi-objective genetic algorithms (GA) include non-preserving elite types and preserving elite types. Preserving elite types preserve a certain percentage of the best solutions from one generation to the next, which aims to maintain a diverse set of high-quality solutions throughout the optimization process. Examples for non-preserving elite type algorithms are Vector optimized Evolutionary Strategies (ES) and Weight Based GA. Examples for preserving elite algorithms are Elitist Non-Dominated Sorting GA (NSGA), Strength Pareto GA, and Pareto-archived ES. NSGA-II [7] and NSGA-III [8] are multi-objective GA that preserve the elites between iterations. NSGA-III has slight improvements over its predecessor. For example, NSGA-III uses crowding distance as a variable to find further solutions to the population and prioritize them to keep diversity.

High dimensionality of datasets creates problems during analysis. These problems can be incorrect results, extended computation times or having results with high complexity to interpret. Dimensionality reduction techniques are used for overcoming these problems. Decomposition techniques focus on finding a lower-dimensional representation that captures most of the variance of the dataset. The most common linear decomposition technique is Principal Component Analysis (PCA). Non-linear techniques extend the linear algorithms to capture the variance of the data in non-linear representations. KernelPCA is an algorithm that extends linear PCA to capture these non-linear representations in lower dimensions [9]. Cross-decomposition techniques are designed to analyze relationships between two or more datasets. They find patterns or connections between variables in different datasets. Unlike decomposition methods, they focus on correlation instead of variance. The most widespread method under this category can be given as Canonical Correlation Analysis (CCA). In the literature, there are dimensionality reduction methods created for MOO applications. Almost all of these methods focus on finding the redundant parts of the datasets. These can be found by finding the correlating vectors of data. One of the methods that uses this approach is PCA-NSGA-II [10]. This method uses the metrics resulting from the PCA method. There are works which compare the performance of these algorithms. Linear and non-linear PCA, δ-MOSS, k-EMOSS and feature selection are some of the widely implemented dimensionality reduction methods for MOO [11, 12, 13].

The location selection problem of coal power plant to nuclear power plant transition includes many different objectives. In order to make a selection, scalarization and objective weighting for finding appropriate objective functions can be done but it could introduce bias. Finding a more reliable method requires MOO algorithms. However, high dimensionality of the problem creates problems for implementation of these algorithms on real world datasets. Different dimensionality reduction methods and optimization strategies have been followed to solve this problem. The objective and novelty in this work are that we propose a general, less biased, and scalable approach for site selection and evaluation that does not require weight assignment by leveraging multi-objective and dimensionality reduction methods. We demonstrate our approach on coal power plant sites that have the potential to host nuclear power plants.

2. ANALYSIS OF THE COAL TO NUCLEAR TRANSITION DATA

2.1. Features of the Dataset

There are 265 US coal power plant sites registered in the INL-NRIC, FPTZ, and STAND database [14]. These locations are given with relevant nuclear power plant siting data. For each location, there is a location ID, longitude, and latitude. The **socioeconomic characteristics of the location** have been given in the next 8 columns. These are "(1) nuclear restrictions, (2) electricity price, (3) net electricity imports, (4) nuclear inclusive policies, (5) positive population sentiment towards nuclear energy, (6) labor rate, (7) social vulnerability index, and (8) existence of nuclear related entities". Each of the data points depends on the county in which the coal power plant is located in. The next 8 columns include the **safety characteristics of the location**. These are "(1) having a near protected land, (2) having a near hazardous facility, (3) fault lines, (4) landslide risk, (5) having low peak ground acceleration in earthquakes, (6) flood risk, (7) being close to open waters and wetlands, and (8) slope. The next 5 columns include the **distance related factors of the location**. These are "(1) distance to a population center, (2) distance to nuclear facilities, (3) having a close R&D center, (4) having an electric substation, and (5) having a transportation system". The STAND data for coal power plants is relatively small with respect to other data analysis problems, but US Department of Energy only reports 157 inactive and 237 active coal power plants suitable for nuclear power plant siting. For this reason, the dataset includes the necessary coal power plant locations for siting analysis.

The initial data was labeled with location ID's. Similar to the research shown at the introduction part, an intuitive weighting research has been done on the dataset by researchers in the University of Michigan in an internal unpublished technical report [15]. The results of that report are reproduced in this paper for convenience and comparison purposes. In that research, each of the objectives mentioned in the previous paragraph has been multiplied with a selected weight. Sum of all weighted objectives gives the final objective value, where the location with the highest sum becomes the best location. **Instead of location ID, the locations in the dataset are labeled with the results of this previous weighting analysis.** The site locations are labelled using the site rank where the best site is labeled with rank 1 and the worst site is labeled with rank 265. For example, the location ID 10684 label was changed to rank label 1, the location ID 2442 label was changed to rank label 2, and so on. *The result of weighting analysis is used as a reference for comparison of different methods in this paper.*

The input dimensions of the data are given as location ID, longitude and latitude. For every location ID, there is only a single longitude, latitude couple. The location data is one dimensional. Applying genetic optimization methods to the input dimensions would not result in meaningful answers since the results are not longitude or latitude dependent, but county and geography related. The MOO methods have been applied to the output dimensions of the dataset. *In other words, the output dimensionality (21) is much larger than the input dimensionality (1), which is what makes this problem challenging and unique compared to traditional optimization problems.*

The dataset has different socioeconomic, safety and distance related objectives. Some of these objectives are aimed to be maximized while some has to be minimized. The objectives labeled with nuclear restrictions, labor rate and also all safety related objectives are changed as minus in the dataset. As a result, the non-dominated sorting (NS) method tries to maximize the objectives while forming the pareto front.

The NSGA-III method requires the application of ES to use a population to get the next population. Since the input dimension of the data is one and does not include meaningful information, ES cannot be applied. NS algorithm of the NSGA-III method has been applied to the 21 output dimensions of the 265 locations.

The result was expected to decrease the dataset to give a smaller pareto front, but the result of the NS includes all 265 locations in the given case. The main reason for this problem is that the number of objectives is too high with respect to the number of data points. Each of the 265 location points is sensitive with respect to at least one objective of the 21 objectives. In order to solve this problem, there are two approaches, the analysis can be done in lower-dimension subsets of the data or dimensionality reduction methods can be applied to the dataset before forming the pareto front.

2.2. Domination and the Pareto Front

The purpose of the methods in the subsequent sections is to form a pareto front of best locations. A pareto front includes the point(s) that dominates other points. Domination is defined as having at least one better objective value without worsening any other objective. In this case, the first pareto front gives the points that dominate the populations of other fronts. The attributes of these points cannot be changed without decreasing an objective. NS method searches through the data points to find the locations which are not dominated by any other point. The points that dominate the entire population except its own front create the first pareto front. The next front is created by the points that dominate the entire population except its own front and the first pareto front, and so on. A demonstration of this process is given in Figure 1.

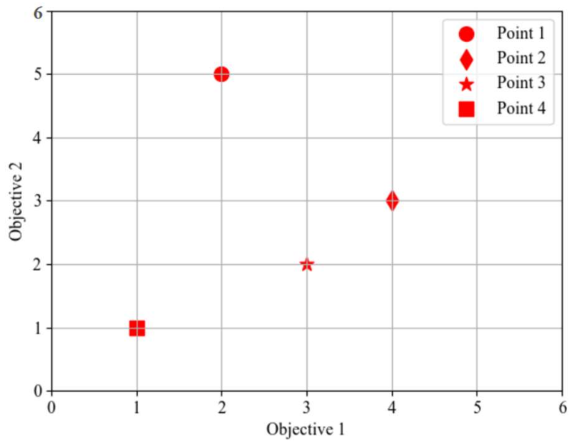

Figure 1. The formation of pareto fronts for selected 2 objectives of the dataset.

In Figure 1, there are 4 points which has different objective values. **The goal is to maximize both objective 1 and 2**. The objective values are the results of 2 different functions for these data points. NS can be used to form the first pareto front from the results of the objective functions. Point 1 has objective 1 and objective 2 values of 2 and 5, respectively. Point 4 has objective values of 1 and 1. It is clear that point 1 is better with respect to both objectives. Point 1 does not dominate point 2 or point 3. However, point 2 dominates point 3 since it has better objective values for both dimensions. In this case, point 1 and point 2 forms the first pareto front. For both of these points, objective 1 or 2 can not be increased without decreasing the other objective. These points form the first pareto front and collectively dominate all the data points in the population except their own pareto front.

2.3. Combinatory Analysis of Objectives

When NS is applied to the whole dataset with 21 objective functions, all the points exist in the first pareto front. There are too many objective functions and each of the points are relevant for some of these objectives separately. For this reason, the first intuitive idea is to try the NS with lower number of objective functions. Arbitrarily chosen 2 objectives from the dataset has been used initially. Pareto front is shown for these 2 objectives. For the combination length of two, there are 210 possible combinations in the dataset. For these two-objective combinations of 21 objectives, 210 different iterations have been run for every two-objective combination. To get the results from these iterations, the number of times a location has been observed in the first pareto front in 210 iterations is counted. The total number observations is reported for each site.

The same approach is repeated iteratively for all lengths of combinations (2-way, 3-way, …, 21-way). For example, for 3-way combinations, the pareto front is formed with first, second and third objectives. Then pareto front is formed with the first, second and fourth objectives. This process is repeated until all possible combination lengths are used. Each combination length has a different number of possible combinations. 3-way objective combinations have 1330 combinations, whereas the 5-way objective combinations have 20349 combinations. The results of each combination length are normalized by the total number of observances for that particular combination length.

For demonstration purposes, the first trial was done with 2 objective functions: Labor cost and electricity price. The result is given in Figure 2. The best front in this figure is given as "Front 0" in the legend. It has the least labor cost and high electricity *market/sale* price. This first pareto front has the locations which an objective cannot be increased without decreasing the other.

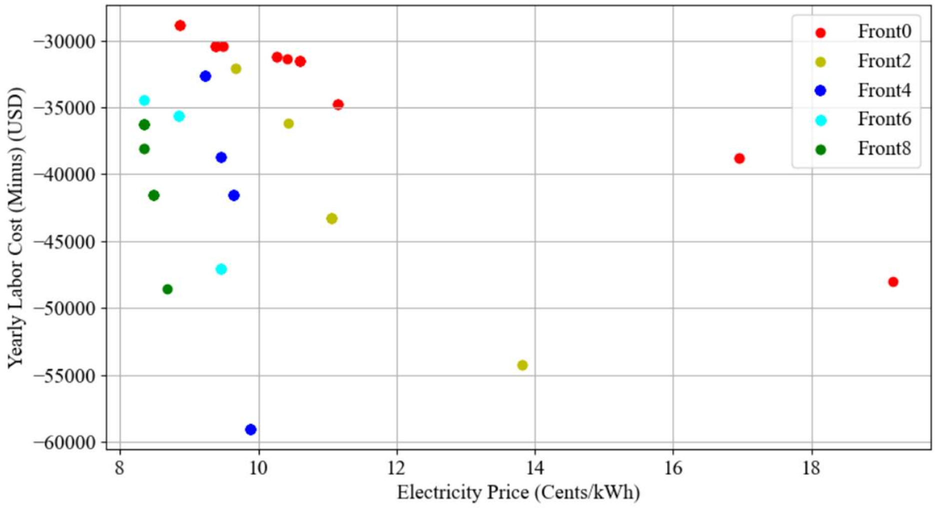

Figure 2. The formation of pareto fronts for selected 2 objectives of the dataset.

The initial two-way objective results rank the following sites as the best: "1, 7, 16, 19, 54, 78, 81, 167, 252". In this result set, each number corresponds to a physical location. The location ID labels are changed with the rank ID resulted of the weighting analysis as explained in the Section 2.1. *Accordingly, the result sets from combinatorial analysis that include the locations with lower ranks will agree with the weighting analysis results.*

NS is able to get the pareto fronts for 2 objectives, even though it could not extract the best locations in the first pareto front when applied on 21 dimensions. To expand the analysis, two-objective combinatorial approach has been applied to the whole dataset. The result for all existing two-objective combinations is given in Figure 3.

Unlike using all 21 objectives at the same time, the results can be easily gathered from the dataset in lower dimensions as shown in Figure 3. When any two objectives are selected, the combinatory analysis evaluates site locations with respect to these objectives. Repeating this process gives all objectives the same importance and continues to search for the site locations that dominate the dataset independent of the selected objectives. However, the length of the combinations is another parameter that affects the result. To make the results independent from the combination length, all possible objective combinations of the dataset should be analyzed.

Each of the objective combinations has a different number of locations in their first pareto fronts. This number increases as the combination length increases. In order to get the results unbiased from the pareto front length of a particular combination length, the results are normalized with **their total number of observations** separately for each combination length. Normalized results are summed to show the mean observance rate of locations independent of the combination length or the mean pareto front length of that combination length. The results are visualized in Figure 4. We can see that sites 1 and 5 show as the best sites in both Figures 3 and 4. However, Figure 4 that includes all combinations lengths ranks sites 9 and 3 as the next two best sites, while the two-way combination test lists sites 21 and 28 in Figure 3.

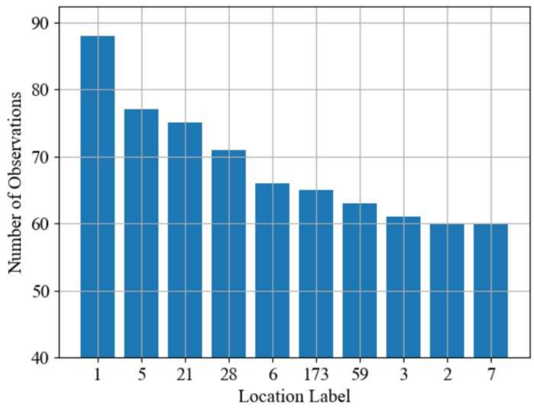

Figure 3. The summed observation rate for two-objective combinations. It shows which sites appear in the pareto front more frequently, considering two-objective combinations of 21 objectives.

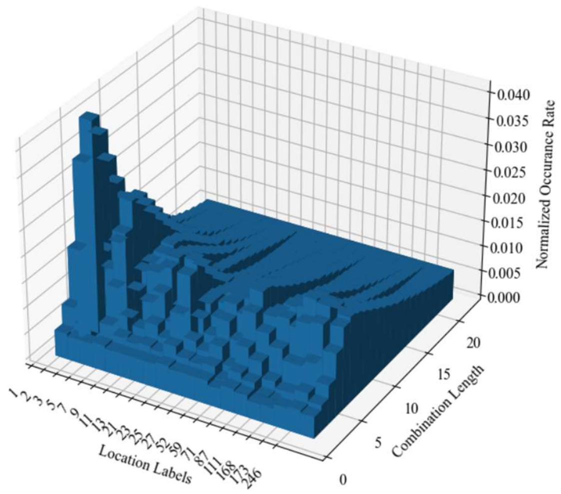

Figure 4. Normalized mean observation rates of locations for all existing objective combinations. The best locations found are: 1, 5, 9, 3 and 11.

2.4. Dimensionality Reduction Techniques

The Siting Tool for Advanced Nuclear Development (STAND) dataset of INL-NRIC, FPTZ has 21 objectives given as data columns. It is difficult to make selections in a real world dataset with many dimensions. The second solution of the problem described in Section 2.1 is to apply dimensionality reduction methods to the dataset. Different types of dimensionality reduction methods are applied to the dataset in this section. Min-Max scaling is applied to the dataset to scale all objectives into [0,1] range in all cases in the following subsections.

2.4.1. Decomposition methods

PCA is one of the most widespread linear decomposition methods for dimensionality reduction. PCA decreases the dimensions by fitting a lower dimensional plane to the data points. The data is represented with respect to this principal component in the results. As the number of resulting principal components decreases, more variance information is lost in this process. The first step of PCA is to get the covariance matrix. The covariance matrix of x and y vectors can be obtained by using Equation 1.

$$cov(x, y) = \frac{\sum(x_i - \bar{x}) * (y_i - \bar{y})}{N} \tag{1}$$

where N is population size, $\bar{x}$ and $\bar{y}$ are mean values, x_i and y_i are data vector elements in the equation.

After obtaining the covariance matrix, eigenvectors and eigenvalues of the matrix are found. The eigenvectors represent the principal components and eigenvalues represent the amount of variance captured by the principal component. The largest eigenvalues and their eigenvectors are chosen. Then the original data is projected onto the principal components by multiplying the data matrix with the chosen eigenvectors.

To analyze the effect of applying PCA on the dataset, socioeconomic, safety and distance related attributes are reduced in dimensions in their own groups. The reduced number of dimensions is selected as 1 in the first case. Eight socioeconomic, eight safety and five distance objectives are decreased to 1 objective for each. The resulting eigenvalues indicate that PCA lost %57.23 of the variance information of the dataset. After dimensionality reduction, NS resulted in 20 locations. When the number of resulting principal components for each group has been increased to two, 6 resulting objectives are obtained. PCA lost %31.55 of the variance information of the dataset. NS resulted in 88 locations which is too large to get a definitive ranking. When the number of principal components for each group has been increased to three, PCA lost %17.26 of the variance information. NS resulted in 217 locations. The result set is still too large to get a meaningful site ranking. In order to decrease the number of locations in the pareto front, combinatory analysis in Section 2.3 is applied to the principal components.

As a non-linear decomposition method, KernelPCA has been selected to be applied to the dataset. KernelPCA chooses a kernel function differently from PCA. Pairwise similarities are computed between all data points. A kernel matrix is constructed. Kernel matrix is used similarly to the correlation matrix in PCA. Kernel function is selected as polynomial and radial basis function (RBF) in two different applications. The KernelPCA method is applied to the data by using the same steps for 1, 2 and 3 reduced dimensions for each group, resulting in 3, 6 and 9 dimensions after the dimensionality reduction, respectively.

2.4.2. Cross-decomposition methods

To change the data type from its original form to a variance-based form also changes the domination structure, which makes it difficult for NS to get the pareto-efficient locations. This problem has been encountered in decomposition-based methods. Canonical Correlation Analysis (CCA) is a multivariate statistical technique that deals with the relationship between two sets of variables. Unlike PCA, which focuses on maximizing variance, CCA aims to find linear combinations of variables in each set that have the highest correlation with each other.

CCA can only be applied between two equal sized datasets. Our data has 21 information columns. However, column 12 only includes zeros. It is a binary value which is flagged if the location had a peak ground acceleration value higher than 0.5g in the past 50 years. None of the site locations were marked for this objective, and so the column can be deleted. The remaining 20 data columns are used to build two matrices with 10 objective dimensions. These two matrices are used as inputs to the CCA. The resulting 10 column data have gone through the same process. First and also the highest valued eigenvalue of each step has been used for reduction. The result of this dimensionality reduction method was a dataset with 5 objectives. Applying NS on the resulting dataset still yielded too many locations. For this reason, combinatory analysis has been done to find the observation rates of each location for every possible objective combination.

2.4.3. Dimensionality reduction techniques for multi-objective optimization

In the literature, there are dimensionality reduction methods designed for MOO. Most of these methods focus on finding the redundant parts of the datasets. This can be done by using covariance to find the correlating vectors of the data. One of these methods is PCA-NSGA-II, which does not directly use PCA but it uses the metrics resulting from the PCA method. The vectors which have the most correlation with others, the ones that contribute to the PCA results less, are found and eliminated. This process is very efficient in mathematical problems with redundant columns or functional dependencies. The plat siting problem is an engineering problem with a real world dataset. The data has very low correlation in its columns unlike these mathematical datasets. It does not have redundant columns. The correlation matrix heat map for the 21 objectives is given in Figure 5 which shows that weak correlation. Since the empty 12th data column has indefinite covariance results, it has been excluded from the matrix.

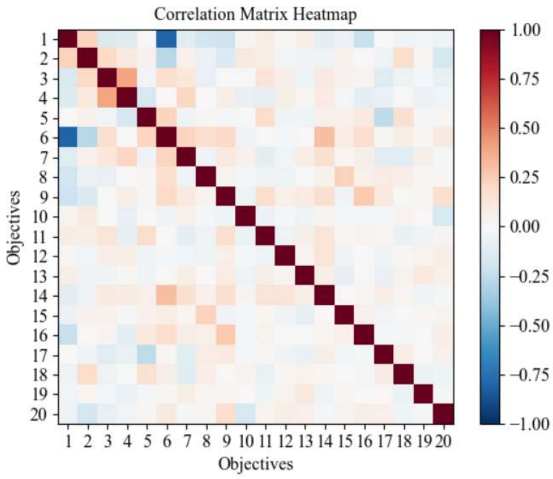

Figure 5. Correlation matrix heat map of the objectives without the empty 12th column.

In the correlation matrix, the highest correlation is found as 0.3919 and lowest covariance is found as -0.7981. As a result, when PCA-NSGA-II is applied to this specific problem, the valuable parts of the data are deleted and lost during redundant column elimination. Even though the domination structure does not change, the points that normally must be in the top performing locations become lost from the final result. The number of data columns decreased from 21 to 14 via this method and combinatory analysis is applied.

In order to show the differences of each method result, the location ranks are collected in a single table. The resulting locations of all methods in Section 2 can be found in Table I. The result which agrees most with weighting analysis result is combinatory analysis of objectives. The top 5 sites in combinatory analysis are: 1, 5, 9, 3 and 11 compared to 1, 2, 3, 4, 5 with weighting analysis.

The weighting analysis is presented as a **reference case** for comparison with other methods presented in the paper. Combinatory analysis results in Table I have 6 locations overlapping with the reference case. This shows that 4 locations of weighted analysis could be a result of a bias in the weights introduced by the analyst. Nevertheless, having six site locations that overlap between weighted analysis and combinatory analysis shows that the weights were selected carefully. There are some locations that perform good in combinatory analysis (e.g. site 58 and 168), but are considered poor in the weighted analysis. These locations may be checked for their relevance.

Table I. Ranks of the best locations for each approach with respect to weighting analysis result.

Weighting Analysis (Reference)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
Combinatory Analysis	1, 5, 9, 3, 11, 59, 168, 2, 246, 7
PCA	13, 19, 149, 170, 205, 259, 101, 166, 200, 6
CCA	2, 103, 149, 215, 220, 12, 205, 225, 5, 13
PCA-NSGA-II	1, 5, 23, 168, 246, 52, 149, 32, 222, 83

PCA-NSGA-II also performed better than common dimensionality reduction methods. PCA-NSGA-II results have 4 locations that overlap with the combinatory analysis results. Since the data columns have very low correlation, the method had difficulties during its redundant objective search. In a real-world engineering data with little correlation, it is harder to apply this method without the loss of valuable data. Nevertheless, its performance is still satisfactory when its results are compared with combinatory analysis results. CCA results have 2 locations overlapping with the combinatory analysis results. PCA results do not have any sites overlapping with combinatorial nor weighting analysis sites. This was also the case for KernelPCA with polynomial and radial basis kernels. PCA changes the data and the domination results of locations. Since PCA and KernelPCA represent the principal components as variance, interpretation of the objectives in the pareto-front becomes challenging. Therefore, PCA and KernelPCA are concluded to be not suitable or effective for this problem compared to other methods.

Lastly, it is worth mentioning that the top five sites identified by combinatorial analysis are: (1) California Argus Cogen Plant, (5) Florida Crystal River Power Plant, (9) Colorado Pawnee Power Plant, (3) New Mexico San Juan Power Plant, and (11) North Carolina Mayo Power Plant. *It is not suprising that California Argus Cogen Plant performs best in the analysis. It has the highest electricity import amount and the highest electricity buying price in the dataset. It has all the geographical parameters as safe. The state has a nuclear inclusive policy and there is an existing nuclear related entity in the county for further installations.*

3. CONCLUSIONS

The site selection problem for nuclear power plants remains a challenging multi-objective problem. During the siting process, socioeconomic, safety-related, and distance-related objectives should be considered. In this work, we proposed a multi-objective optimization methodology that can aid in reactor siting evaluation independent from weight assignment or human intervention. The methodology was applied to the coal plant sites available in STAND tool, which have the potential to host a nuclear power plant. Our examination using non-dominated sorting in combinatorial analysis revealed that 6 out of 10 coal sites align with the conventional analysis employing predetermined weighting. However, we identified four sites that, despite not being highly ranked in the predetermined weighting approach, exhibit promise and may be explored further. Certain dimensionality reduction techniques demonstrated satisfactory site ranking in comparison to combinatorial analysis, whereas principal component analysis failed to consistently rank sites as effectively as other methods. Future efforts will involve extending this methodology to assess additional sites within the NRIC/STAND database, such as Brownfield sites, and determining the competitiveness of the coal sites identified in the INL report [2] against other sites suitable for nuclear applications.

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