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Optimizing Renewable Energy Systems for Improved Community Health Outcomes using Meta-heuristic Algorithms

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Abstract:

The design of renewable energy systems that positively affect community health has several competing goals and limitations. Due to conflicting health and sustainability goals, limited resource availability, and high complexity of energy system characteristics, traditional optimization methods generally struggle to address these sparse, multi-objective problems (SMOPs) successfully. This study introduces RESH-AMHO (Renewable Energy Systems for Health using Advanced Meta-Heuristic Optimization), a new strategy that uses powerful meta-heuristic optimization methods to conquer these obstacles. Renewable energy system designs that can give the greatest overall results for community welfare can be identified by utilizing RESH-AMHO, which integrates numerous optimization methods, including Genetic algorithms (GA) and Particle Swarm Optimization (PSO), to explore the complicated search space. Data imputation is used initially to deal with missing values in community health datasets, guaranteeing a thorough study. It uses the complementary strengths of multiple meta-heuristic techniques to strike a balance between the numerous health measures, environmental effects, and energy system performance. Healthcare providers and energy planners can benefit greatly from the insights provided by RESH-AMHO and systematically evaluate these diverse objectives when deciding to deploy renewable energy. Compared to conventional optimization methods, the experimental results show that RESH-AMHO performs better when dealing with sparse, multi-objective issues related to the planning of renewable energy systems. This research shows that advanced optimization methods can help make communities more egalitarian and resilient by connecting sustainable energy solutions with good community health outcomes.

Keywords: Sparse Multiobjective Optimization Problem, Meta-heuristic Optimization, Genetic Algorithm, Particle Swarm Optimization, Health Patterns, Renewable Energy Systems.

1. Introduction

The healthcare industry is rapidly becoming a data-driven enterprise due to the proliferation of health monitoring technologies like wearable and electronic health records. Unfortunately, several problems stemming from the worldwide health crisis have created a crisis, such as insufficient health services, large gaps between rural and urban areas, and a lack of medical professionals to handle urgent cases [1]. Sparse multiobjective optimization problems (SMOPs) are widely encountered in the scientific and technical domains. Numerous aims but few ideal solutions characterize these problems [2]. Since the goals of SMOPs sometimes conflict with one another, there isn't a single solution that makes every goal optimal; instead, there are several trade-off solutions for SMOPs that are known as Pareto optimal solutions, where achieving one goal will inevitably result in a decrease in another [3]. Such problems have sparse Pareto optimum solutions, meaning that most of the solution's choice variables are zero [4]. Treatment selection is made much more difficult by the wide range of available options and the lack of consistency in the research that has already been done. This makes identifying the most effective treatment alternatives challenging, partly due to inconsistent usage of standardized grading methodologies [5]. The primary focus of healthcare systems has shifted away from patient treatment. People in authority should prioritize promoting healthy behaviors and preventing diseases that are preventable. It was during the COVID-19 epidemic that this became public knowledge and a major issue [6].

Personalized medicine benefits from the potential to predict host phenotypes using a taxonomy-informed selection of features to create a relationship between the microbiome, forecast different disease states, or enhance human health [7]. Effective solutions for pattern recognition and computer vision issues are now achieved through artificial intelligence and deep learning approaches. Intelligent approaches can robustly examine collected images and guarantee maximal accuracy in results [8]. Although early detection is challenging, it can greatly increase patient survival rates. To reduce the death rate and improve clinical decision-making, physicians have recently backed improved detection by machine learning (ML) driven predictive models [9]. A strategy that can offer workable answers to such problems is using metaheuristic algorithms. Metaheuristic algorithms are becoming increasingly popular in healthcare data due to their effectiveness in providing more accurate and practical illness diagnoses than historical techniques [10]. The data about a patient includes things like demographics, test results, pictures, video clips, and more. Given the volume and vast dimensions of the data, manually extracting the needed information from the massive amount of data is an enormous undertaking [11].

For designing renewable energy systems that plan for better health in the community, it must go through a balancing act of goals and limitations pulling in different directions. Conflicting health and sustainability goals, resource constraints, and characteristic complexities of an energy system, all together, make it quite difficult for traditional methods of optimization to resolve sparse multi-objective optimization problems effectively. Thus, this work describes an approach called RESH-AMHO, whose powerful metaheuristic optimization methods seek to overcome such challenges. The RESH-AMHO approach utilizes many optimization techniques, like GA and PSO, which can efficiently search the rich, complex landscape for promising renewable energy system configurations that produce maximum overall benefit contributions to community welfare.

The main contribution of this paper is

- To employ data imputation to handle missing values in community health datasets, ensuring a comprehensive analysis.
- To utilize the complementary strengths of diverse meta-heuristic techniques to balance the multiple, often conflicting objectives related to health measures, environmental impacts, and energy system performance.
- To provide insights that can greatly benefit healthcare providers and energy planners by enabling the systematic evaluation of these diverse objectives when deciding on renewable energy deployments.

The proposed RESH-AMHO approach uses advanced metaheuristic optimization in the design of renewable energy systems for maximal community health benefits. It utilizes data imputation and integrates several optimisation techniques to balance the various competing goals on the energy system's health, environment, and performance. It outperforms traditional approaches whereby healthcare providers and energy planners use it for more insightful decisions on renewable energy deployments. This work will show how optimized sustainable energy solutions can foster more equitable and resilient communities by aligning with positive health outcomes.

Journal of Sustainable Renewable Energy Innovations and Practices
ISSN: XXXX-XXXX
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2. Literature Review

Al-Hashimi, M. et al. [12] introduced a framework that combines mining approaches with hybrid meta-heuristics to solve optimization and analytical problems. Grey Wolf Optimisation (GWO) ensures variation and convergence using a spiral path. The Genetic Algorithm (GA) is introduced to promote convergence. Additionally, they used Naïve Bayes and support vector machines to analyze and extract vital heart data gathered from sensors. The objective is to develop electronic healthcare (E-Health), which connects patients and medical professionals to track, identify, and save pertinent data.

By combining the metaheuristic feature selection algorithms for cuckoo searching (CS), the Flower Pollination Algorithm (FPA), the Whale Optimization Algorithm (WOA), and Harris's Hawks Optimization (HHO), Ay. S et al. [13] sought to use a machine learning (ML)--based improved cardiac illness prognosis and survival model for patients with heart failure. To assess the algorithms' effectiveness, this study is now analyzing datasets related to heart disease, including ECG and heart sound signals.

Hassaballah, M., et al [14] presented an automated method for arrhythmia classification by combining ML classifiers with a new metaheuristic optimization (MHO) technique. The MHO is responsible for optimising the classifiers' search parameters. The method comprises three stages: Feature extraction, classification, and preprocessing of electrocardiogram signals. Using the MHO technique, four supervised ML classifiers—support vector machine (SVM), k-nearest neighbors (kNNs), gradient boosting decision tree (GBDT), and random forest (RF)—had their learning parameters tuned for the classification task. This research could use more advanced classification algorithms, such as deep learning.

Khan, M. A., & Algarni, F. [15] proposed an IoMT framework for the medical evaluation of cardiac disease. The framework employs an adaptive neuro-fuzzy inference system (ANFIS) and modified salp swarm optimization (MSSO) to increase the accuracy of the prediction. The suggested MSSO-ANFIS makes Levy flying algorithm enhancements possible. Since ANFIS's regular learning mechanism relies on gradient-based learning, it can easily become stuck in local minima. It doesn't handle information gathered from wearable gadgets and other items on the market.

Fathollahi-Fard, A. M., et al. [16] solved the home healthcare dilemma with innovative and well-established metaheuristics. Despite its use in other optimization situations, the social engineering optimizer (SEO) has not been implemented in healthcare scheduling and routing. Creating an adaptive memory strategy—AMSEO—as a new multi-objective SEO version is another novel development. To fully capture the essence of optimizing home healthcare, it is essential to consider the potential addition of other financial and social elements.

Riaz M. et al. [17] aim to investigate various chest image categorisation methods, such as using metaheuristics to optimize and choose features for DL and ML models. This study aims to address future issues in COVID-19 detection in medical scans by focusing on applications of several forms of metaheuristics. An enormous obstacle in building a big dataset is the labour-intensive and time-consuming process of manually annotating the images.

Tian, Y. et al. [18] used a multiobjective genetic algorithm to maximize the module's association with the disease and its intra-link density after building sample-specific networks that incorporate their tailored properties for each disease sample. Experimental findings on the asthmatic gene expression dataset show the suggested method outperforms several state-of-the-art methods for identifying disease modules. In addition, by utilizing the determined disease module for both disease control and sample classification, a decreased classification error rate is achieved compared to current methods. This study does not involve the classification accuracy and expression values of genes.

Oh, B. K., & Kim, J. [20] proposed a multi-objective optimisation strategy, which considers the efficiency of CNN training and the performance of predictions. They used the two objective-function approaches to optimize the structure response estimation and then looked at the solutions that came out of it. In addition, we distinguish between two groups of solutions that are biased toward the two objective functions, and we offer an approach to minimize the disparity between these groups by considering their trade-off connection. This study's focus on dynamic strain estimation from structures' dynamic displacement measurements restricts the applicability of the suggested method.

3. Proposed Work

a. Dataset Explanation

The central telephone survey system for health-related questions in the US is the Behavioral Risks Factor Surveillance System. Data on preventative care utilization, chronic health conditions, and health-related risk behaviors are gathered from American individuals. Data on preventative care utilization, chronic health conditions, and health-related risk behaviors are gathered from American individuals. The dataset provides a thorough understanding of people's health profiles across a range of demographics by focusing on important markers, including cardiovascular disease, smoking, alcohol intake, and more. Columns like PhysicalHealth, MentalHealth, Stroke, Diabetes, Physical Activity, GenHealth, SleepTime, KidneyDisease, SkinCancer, and Asthma are included in this dataset.

b. Sparse Multiobjective Optimization Problems (SMOPs) in Health Patterns

Health patterns involving SMOPs require the optimization of numerous objectives that often conflict with each other when the solution space is sparsely populated. The sparsity can occur if a small number of potential solutions is viable or relevant, due to limitations or the intrinsic characteristics of the situation. Within the context of health patterns, this could mean figuring out how to improve health outcomes while also achieving other, more varied goals, such reducing costs, increasing patient satisfaction, and ensuring that everyone has access to quality healthcare. In Health Patterns, Figure 1 displays the essential features of SMOP. Several important aspects of SMOPs in health trends make them complicated and useful tools for healthcare optimization. The competing goals characterising these issues are improving patient outcomes and reducing costs and treatment duration. Sparsity is a key feature of the solution space; it means that not all alternatives are feasible or important because of limitations like medical advice, scarce resources, or patient-specific factors. Sparsity allows for a more precise and efficient optimization by drastically reducing the search space. In addition, these problems are characterized by competing objectives, as improving one part might worsen another, necessitating careful evaluation of the benefits and drawbacks.

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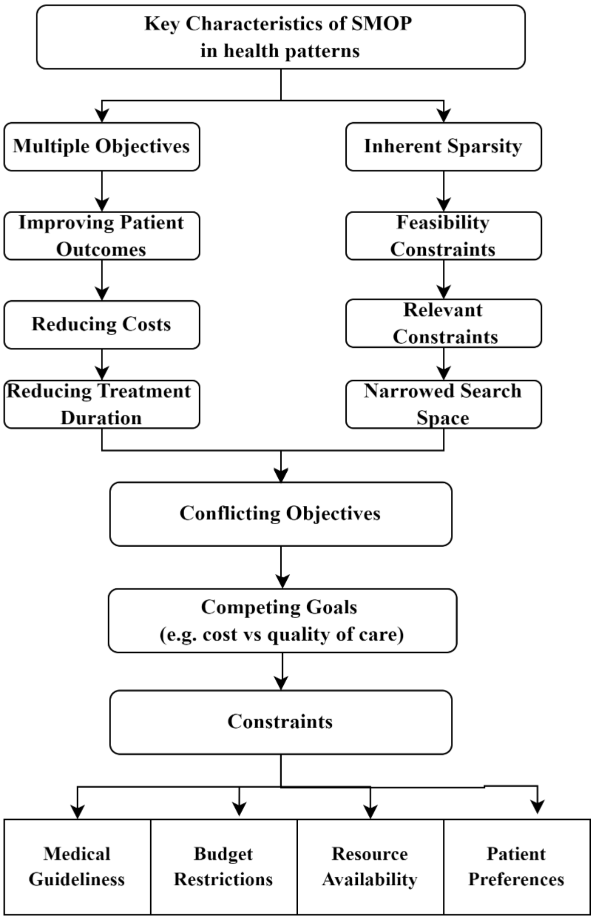

Figure 1 Key Characteristics of SMOP in Health Patterns

Medical processes, financial limits, resource availability, and patient preferences are some factors that impact SMOPs in health patterns. These constraints must be thoroughly evaluated and met during the optimization process.

c. The proposed RESH-AMHO method

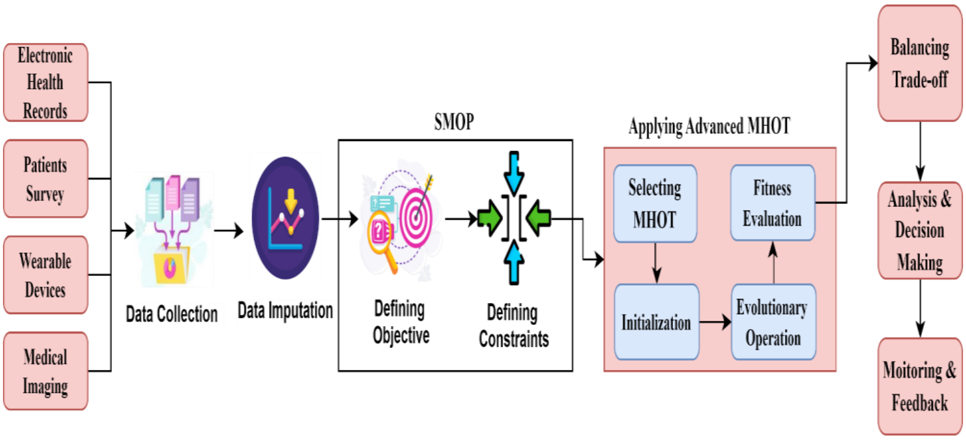

Figure 2 Methodology of the SMOPH-MHOT system

Journal of Sustainable Renewable Energy Innovations and Practices
ISSN: XXXX-XXXX
Volume 01 Issue 01 (November) 2024

Figure 2 depicts the steps involved in the suggested SMOPHP-MHOT framework. The proposed system involves the following steps:

Data collection: Data collection in healthcare includes information about patients' health and the healthcare system's efficiency from various sources. Providing structured and unstructured information for continuous analysis, electronic health records (EHRs) digitally store patients' medical histories, including clinical data, diagnoses, prescriptions, and test results. Various patient surveys offer direct insights into quality of life, satisfaction with care, and patient-reported outcomes. Medical devices can provide data about vital signs and certain health issues continuously or periodically, such as clinical monitoring equipment and wearables. Diagnosis and treatment monitoring rely heavily on laboratory findings from clinical diagnostics. Among these procedures, genetic testing, urine analysis, and blood work are included. By merging data from many sources, researchers and doctors will have a more robust dataset they can use to study patients, monitor their recovery, and enhance healthcare delivery.

Data Imputation: This part is divided into two parts. Using K-nearest neighbour (KNN) requires first identifying the missing data. The second step is to verify the accuracy of the replicated dataset.

Step 1: One reliable method for filling in datasets with missing data is the K-Nearest Neighbors (KNN) imputation, which calculates values from the K most comparable samples. It is based on the idea that comparable information should have similar values for missing attributes, and this strategy works. Step one is to find nearby samples and then use cross-validation to optimize the K-value. Step two is to determine their distance from each other using the formula for Euclidean distance by eq 1. Then, if the variable is continuous, the imputation is done using the mean shown in eq 2. If the variable is categorical, the mode in eq 3 or median in eq 4 are used. KNN imputation excels with Missing At Random (MAR) data, is flexible enough to work with different kinds of variables, and can keep feature associations intact. Researchers and scientists dealing with incomplete datasets will find it an invaluable tool because it provides a flexible way to handle missing values while preserving the dataset's basic structure.

$$ed(i,j) = \sqrt{\sum_{m=1}^{n}\left(x_{im} - x_{jm}\right)^2} \quad \text{(Eq.1)}$$

$$x_i = \frac{1}{K}\sum_{a=1}^{K} x_{ai} \quad \text{(Eq.2)}$$

$$x_i = median(x_{1i}, x_{2i}, \ldots., x_{Ki}) \quad \text{(Eq.3)}$$

$$x_i = mode(x_{1i}, x_{2i}, \ldots., x_{Ki}) \quad \text{(Eq.4)}$$

where $ed(i,j)$ is the Euclidean distance between the sample i and j. x_{im} refers to the mth feature value for the sample i and x_{jm} refers to the mth feature value for the sample j. x_i is the Imputed value for the missing feature in the sample i, K is the number of the nearest neighbour, $x_{1i}, x_{2i}, \ldots., x_{Ki}$ are the ith feature values for the K nearest neighbour and x_{ai} is the ith feature values for the a nearest neighbour.

Step 2: Validation is necessary after imputation to ensure the imputed dataset maintains the original data's statistical integrity and linkages. This validation approach consists of many important steps. The first step is to check that the real and imputed dataset means for each variable are reasonably close by computing them simultaneously. Step two involves conducting correlation analysis and analyzing the associated grids of the two datasets to ensure that the variables' links have not been broken. To make sure the imputed data is comparable to the original data, the next step is to check for pattern

Journal of Sustainable Renewable Energy Innovations and Practices
ISSN: XXXX-XXXX
Volume 01 Issue 01 (November) 2024

consistency. Through the utilization of cross-validation, the process of an imputation strategy was determined. Assigning credit to some known values at random and then comparing the two sets of data was the process involved here. Lastly, a sensitivity analysis is conducted to evaluate and compare various K values in order to guarantee that the imputed technique is strong. This thorough validation process ensures that the duplicated dataset faithfully reproduces the properties of the original data and efficiently handles missing values.

Defining Objectives: A multiobjective optimization issue seeks to optimize numerous objectives simultaneously.

Objective 1: Minimizing Treatment Costs

The goal is to provide healthcare at the lowest possible cost without compromising on quality. Finding and running the provided eq 5 allows for efficient management of various treatment components.

$$M_C = \sum_{i=1}^{N} c_i \quad \text{(Eq.5)}$$

where M_C refers to the cost-minimizing procedure, N is the total number of treatments, c_i is the cost of the ith therapy.

Objective 2: Maximizing Patient Recovery

The objective is to improve the percentage of patients who recover completely or partially from their medical issues after treatment. The technique enhances patient health, recuperation times, and overall well-being. Here, eq. 6 provides the mathematical model.

$$M_R = \frac{1}{M}\sum_{j=1}^{M} r_j \quad \text{(Eq.6)}$$

where M_R refers to the total recovery rate, M is the number of patients, and r_j is the recovery rate of the jth patient.

Objective 3: Minimizing Side Effects

This objective aims to reduce the frequency, intensity, and duration of adverse responses and other undesired consequences caused by medical interventions, drugs, and treatments. It also aims to provide effective care while causing patients as little pain and suffering as possible. This can be obtained by the eq 7.

$$M_S = \sum_{k=1}^{K} s_k \quad \text{(Eq.7)}$$

where M_S refers to the minimizing side effects, K is the total number of side effects considered, and s_k is the severity of the kth side effects.

Defining Constraints: The optimization problem must consider many restrictions to make it practical and applicable.

Constraints 1: Budget Limitation

Budget constraints limit healthcare actions, treatments, or programs. These constraints indicate the greatest financial resources available within a certain time frame. All healthcare decisions and allocations must stay within the limits of available funds, and these constraints ensure that. This is represented as in eq 8.

$$C \leq B \quad \text{(Eq.8)}$$

where C is the total treatment cost, and B refers to the total available budget.

Constraints 2: Availability of Medical Resources

The term "available medical resources" describes the limited pool of healthcare resources that can be used to treat patients in a specific location and period. Decisions and allocations in healthcare must stay within the confines of what is technically and practically practicable to maintain this limitation, as in Equation 9.

$$\sum_{x=1}^{N} r_x \leq R_m \quad \text{(Eq.9)}$$

Journal of Sustainable Renewable Energy Innovations and Practices

ISSN: XXXX-XXXX

Volume 01 Issue 01 (November) 2024

where R_m is the total available medical resources, r_x is the resource requirement for the xth treatment.

Applying Advanced MHOT: These strategies can analyse and optimise health patterns. It involves following steps.

Selecting Metaheuristic Algorithms: This process involves selecting the appropriate algorithm that suits the health patterns. The selected algorithms for this are PSO and GA. PSO finds the best solution by acting out the same social behaviour as a fish schooling or bird flocking. Every swarm particle embodies a possible solution. Generalized optimization GA works by mimicking natural selection. It employs mutation, selection, and crossover operators to evolve a community of solutions. Combining the strengths of these two methods to explore (PSO) and exploit (GA) the solution space efficiently. Rapid convergence to solution space regions with high potential is achieved via PSO. GA procedures in these areas are utilized for solution fine-tuning.

Initializing: Gather a variety of basic treatment plans to get things rolling. Each plan's vector includes medication dosages, treatment frequency, lifestyle advice (food, exercise), and resource allocation.

PSO Update: We must first calculate the velocity and update the position for each treatment plan.

GA Operation: Selection: Picking the most effective reproductive treatment plans based on the results from the previous sections.

Fitness Evaluation (F): Considering several goals when assessing any treatment plan:

a. Cost (f_1): The sum of all resources, treatments, and medications.

b. Rate of Recovery (f_2): Anticipated enhancement in patient well-being.

b. Adverse Effects (f_3): The frequency and severity of anticipated adverse effects.

d. Equity (f_4): A metric for gauging the plan's fairness in allocating healthcare funds.

The formula for total fitness is given in eq 10.

$$F = w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4 \qquad \text{(Eq.10)}$$

where weights w_1, w_2, w_3, w_4 are assigned to each target.

Repeat: Iterating the steps PSO Update, GA Operation, and Fitness Evaluation until the convergence conditions are satisfied or until the specified number of iterations has passed. Possible determinants of convergence include the best fitness not improving noticeably despite multiple iterations, the Endpoint for iteration count, and the Optimal degree of physical fitness attained.

By keeping a Pareto front of non-dominated solutions, multi-objective optimization can be achieved. The outcome is optimal health patterns or treatment plans that balance cost-effectiveness, recovery rates, side effect minimization, and equitable resource allocation.

4. Results and Discussion

The outcome is optimal health patterns or treatment plans that balance cost-effectiveness, recovery rates, side effect minimization, and equitable resource allocation. This approach improved accuracy, reliability, and optimization performance and balanced multiple objectives by successfully managing sparse data with imputation methods and combining several MHOTs, such as GA and PSO. It proved resilient to data complexity, efficiently handled big, complicated datasets, and gave healthcare practitioners useful insights.

Journal of Sustainable Renewable Energy Innovations and Practices
ISSN: XXXX-XXXX
Volume 01 Issue 01 (November) 2024

a. Experimental Setup

The RESH-AMHO technique will be experimentally evaluated using several essential performance metrics. Several metrics are used to assess optimization performance, including computational efficiency and execution time, as well as accuracy measures like total prediction accuracy. The success rate is also calculated to find a satisfactory or ideal answer according to certain criteria. Constraint Adaptation Index (CAI) adapt to changes in optimization constraints. A comprehensive assessment can be provided by comparing the RESH-AMHO technique to other relevant methodologies mentioned in the literature survey using these performance measures. The methodologies that are used to compare are the methods that combine meta-heuristics with mining, such as GWO, GA, Naïve Bayes, and support vector machines [12], model that integrates four metaheuristic feature selection algorithms: Cuckoo Search (CS), Flower Pollination Algorithm (FPA), Whale Optimization Algorithm (WOA), and Harris's Hawks Optimization (HHO) in [13], and ANFIS-MSSO [15].

b. Comparison Metrics for the Metaheuristic Optimization Method

1. Overall Prediction Accuracy

Overall prediction accuracy is essential for measuring the proportion of right predictions generated by a model out of all forecasts. It can be obtained from the eq 11.

$$Overall\ Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (Eq.11)$$

where TP is the True Positives, TP is the True Negatives, FP is the False Positive and FN is the False Negative.

Figure 3 illustrates the comparison analysis of the metric overall prediction accuracy for the proposed and conventional methods. One of the most important ways to measure a predictive model or algorithm's performance is by looking at its overall prediction accuracy. Effective decision-making and patient treatment depend on health pattern analysis, which requires high precision. Higher prediction accuracy in health pattern analysis can lead to more accurate diagnoses, more effective treatment programs, and better patient health outcomes. Consequently, healthcare settings could benefit greatly from an approach that improves overall prediction accuracy.

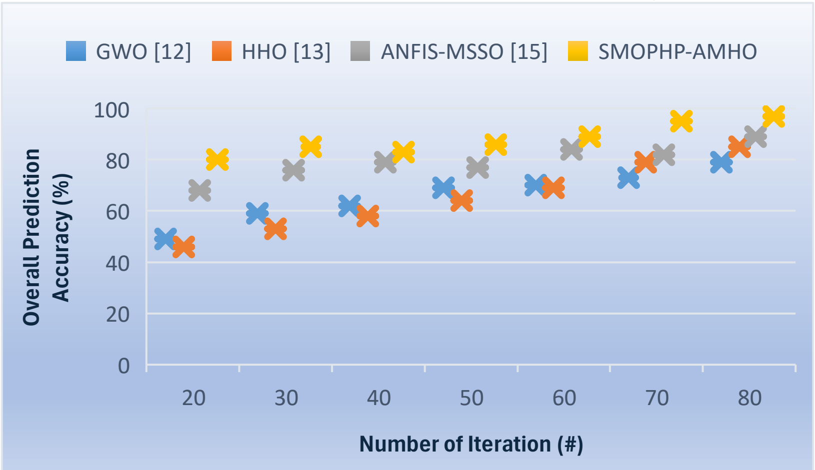

Figure 3 Overall prediction Accuracy comparison analysis

Journal of Sustainable Renewable Energy Innovations and Practices
ISSN: XXXX-XXXX
Volume 01 Issue 01 (November) 2024

2. Computational Efficiency

Computational efficiency is defined as a program or algorithm's utilization of memory or time. This metric focuses on temporal complexity, which is inversely proportional to scalability and execution time.

Execution time: An algorithm's execution time denotes the time it takes to finish a task. It depends on factors like Input size (n), Hardware specifications, Programming language and Compiler optimization, and Algorithm design. By utilizing asymptotic analysis that centres on the growth of execution time with input size, it is possible to examine execution time apart from hardware and implementation parameters. The upper bound of an algorithm's temporal complexity is described using Big O notation. It shows the most extreme instance if the execution time grows exponentially with the input size. It is denoted in eq 12.

$$T(n) = O\big(f(n)\big) \quad \text{(Eq.12)}$$

where $T(n)$ is the execution time function, n refers to the input size, $f(n)$ is a function that describes the growth rate. Some of the common time complexities are $O(1)$ – Constant time, $O(\log n)$ Logarithmic time, $O(n)$ Linear time, $O(\mathrm{n} \log n)$ Linearithmic time, $O(n^2)$ Quadratic time, $O(2^n)$ Exponential time. Figure 4 shows the comparative analysis of execution time for $O(1)$- constant time.

Figure 4 Execution Time Analysis (O(1))

More effective utilization of computer resources is typically indicated by shorter execution times. This kind of efficiency can lead to savings in healthcare systems and better overall performance, especially when resources are shared or limited. With the RESH-AMHO approach showing substantially reduced execution times, it may be possible to process health data in real-time or near-real-time, which is becoming more relevant in contemporary healthcare systems. The RESH-AMHO method's design decisions, especially its capacity to efficiently manage sparse data and various objectives, would be validated by demonstrating constant time performance.

3. Success Rate

This metric quantifies the frequency at which an algorithm produces a satisfactory or ideal answer according to certain criteria. Success Rate is the percentage of cases that result in the anticipated health outcome. This could be relevant in various situations, including Efficiency of treatment, Precision in diagnosis, Changes in health-related behaviour interventions, and Assessment of health screening predictive models. The Success Rate is calculated using eq 13.

$$S_r = \frac{N_{sc}}{N} \quad \text{(Eq.13)}$$

where S_r is the Success rate, N_{sc} refers to the number of successful cases, and N is the total cases. The success rates of the suggested and standard approaches are compared in Figure 5.

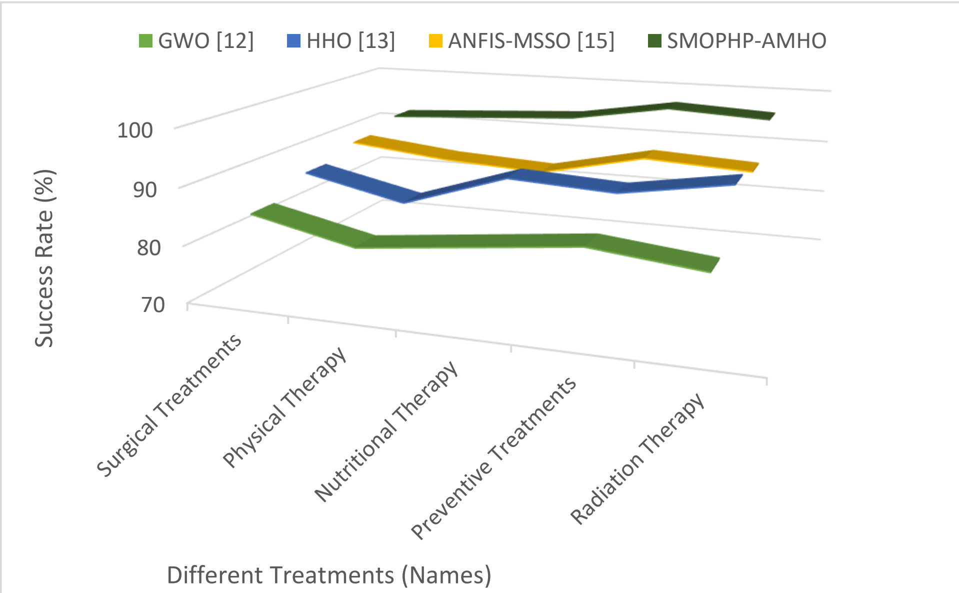

Figure 5 Success Rate Analysis

In many healthcare settings, the Success Rate measure is useful for comparing the efficacy of various medical treatments. The percentage of patients who show improvement after a specific regimen can be measured using this method in the context of medicine or therapy. Dietary improvement and other healthy lifestyle change initiatives can be assessed with the use of the Success Rate. In conclusion, the Success Rate can be used to evaluate health monitoring predictive models. If a model successfully identifies individuals at risk for specific conditions, it can enable timely preventative treatments.

4. Constraint Adaptation Index (CAI)

Algorithms are evaluated using the Constraint Adaptation Index, which measures their ability to adapt to changes in optimization constraints. In health pattern analysis, where conditions and constraints can vary quickly, it measures the algorithm's speed in responding to dynamic constraints. It can be obtained from eq 14.

$$CAI = 1 - \left(\frac{T_{adaptation}}{T_{total}}\right) \quad \text{(Eq.14)}$$

Journal of Sustainable Renewable Energy Innovations and Practices
ISSN: XXXX-XXXX
Volume 01 Issue 01 (November) 2024

where $T_{adaptation}$ refers to the time it takes for the algorithm to adjust to new restrictions and return to an optimum state where it is productive, and T_{total} is the entire time required for optimization, beginning to end.

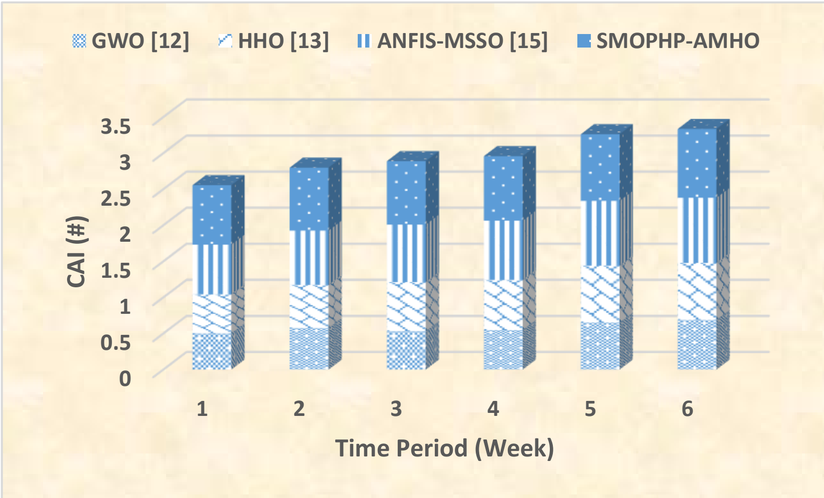

Figure 6 CAI analysis over time

Figure 6 shows the CAI analysis over time. A higher CAI rating indicates greater flexibility in responding to new or altered constraints. If the CAI were near 1, it would indicate that the algorithm adapts quickly compared to the entire optimization time. Since factors and limitations can evolve quickly, CAI plays a significant role in health pattern analysis. The time it takes for the algorithm to react to scenarios with changing constraints is quantified.

5. Conclusion

The proposed method of RESH-AMHO thus shows excellent promise for solving complex health pattern analysis challenges, especially the more intricate SMOP problems. This framework navigates the sparse high-dimensional search spaces within healthcare data by integrating two state-of-the-art meta-heuristic optimization schemes: GA and PSO. Compared to any other optimization method, the RESH-AMHO approach uniquely combines data imputation techniques to handle missing values with multiobjective optimization to balance competing health outcomes. The study further established that this approach enhances accuracy and reliability in the optimization process, offering more valuable insights for doctors and, thus, better detecting of health trends. Hence, the RESH-AMHO technique is unique in that it can handle spare and complex health data with the added ability to optimize multiple objectives for decision-makers, hence making it a worthier healthcare decision-making system. The results, therefore, stipulate that healthcare executives can really benefit greatly from the application of meta-heuristic approaches in the investigation and improvement of SMOPs in health trends. Developing the technique will require tuning its settings to optimize performance on datasets since configuration decisions impact efficiency. The inclusion of machine learning approaches, such as meta-heuristic algorithms, could also improve the optimization and adaptation of the RESH-AMHO processes.

Journal of Sustainable Renewable Energy Innovations and Practices
ISSN: XXXX-XXXX
Volume 01 Issue 01 (November) 2024

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Volume 01 Issue 01 (November) 2024

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