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Optimized Hybrid Renewable Energy Systems for Sustainable Electric Vehicle Charging Infrastructure: A Modified Metaheuristic-Based Techno-Economic Analysis Across Geographically Diverse Indian Regions

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Abstract—This is an all-inclusive study examining the technical feasible and economic possible possibilities of grid-connected hybrid renewable energy systems with electric vehicle charging stations (EVCS) installed in three geographically dispersive areas in India. The energy-efficient algorithm (MSSA) a new modified salp swarm algorithm (MSSA) is applied and optimized with Levy Flight distribution and optimized particle swarm optimization (PSO) to optimize the system component sizing and minimizes the total net present cost (TNPC) and leveled cost of electricity (LCOE). System modeling and optimization is done by using the MATLAB-based simulation platform. The research fills critically important research gaps by comparing the complementary wind and solar resources in New Delhi, Ahmedabad, and Madurai, which have conflicting potentials of renewable energy. Findings indicate New Delhi gives the most cost effective set-up with TNPC of 14,853.63 and LCOE of 0.0051/kWh with MSSA. Optimized PSO method has an equivalent performance with improved convergence properties with 35 percent reduction of the number of computational iterations than MSSA without compromising the quality of the solution. The best system has 120 solar photovoltaic panels (325 W rated capacity) and 310 wind turbines (650 W rated capacity) with a production of 591,117 kWh/annually with 64.5 percent contribution of the wind and 33.5 percent contribution of the solar energy. When comparing Ahmedabad with Madurai, it can be concluded that the city of Ahmedabad needs significantly varied optimization settings when it comes to the exceptional coastal wind strengths, whereas Madurai is portrayed with balanced solar-wind complementary. Both MSSA and optimized PSO show better convergence properties than the traditional algorithms. Through sensitivity analysis, it can be seen that feed-in tariff structure and discount rates play a very crucial role in the economic performance. The study offers evidence-based policy formulation aid to policymakers and utility providers intending on building sustainable EV charging infrastructures in developing countries, whose findings can be applied to renewable energy penetration in transport electrification projects.

Index Terms—electric vehicle charging, hybrid renewable energy system, solar photo-voltaic, wind turbine, battery energy storage, metaheuristic optimization, modified salp swarm algorithm, optimized particle swarm optimization, MATLAB simulation, leveled cost of electricity, net present cost, sustainable transportation, India.

I. INTRODUCTION

A. Global Context of Transportation Electrification and Renewable Energy Integration [1]

The transport industry in the world contributes to some 27 percent of energy related carbon dioxide emission and road vehicles are the major contributors to these emissions. The emissions of greenhouse gases concerning transportation, according to the International Energy Agency, have soared by 60 percent since 1990, and poses a desperate sense of urgency to reduce the problem through radical technological and systemic changes. At the same time, there has been a major shift in the global electric generation profile, as now approximately 29 per cent of energy is generated by renewable means, a trend that was 22 per cent in 2010. This energy transitional environment opens up new transformational possibilities of electrification of transportation in connection with renewable energy infrastructure development.

EV is an important technology initiative that can enable significant carbon emission mitigation. Lifecycle analysis shows that a vehicle driven with renewable electricity will reduce carbon emissions by more than 60 percent as compared to the traditional internal combustion engine car. The technical feasibility of EV technology is proven beyond any doubt, and the modern energy density of the battery, state of the art charging infrastructure, and the performance features of the vehicle models have taken into consideration the past consumer anxiety towards the technical features of the vehicle discussed as range and the time of charge.

Nevertheless, the environmentally friendly properties of transportation electrification heavily depend on the source of electricity which will be used to charge transportation infrastructure. The environmental gains of EVs are significantly reduced in areas where coal and fossil fuel use prevails as electricity making areas as in India. This fact has prompted increasing scholarly and policy interest in integrated renewable energy-EV systems, where renewable energy resources

directly drive EV charging systems, both accomplishing transportation decarbonization and renewable energy growth at the same time.

B. India's Transportation Electrification Landscape [2] [3] [4]

India, being the second-largest population hub in the world and having a population of more than 1.4 billion, with the economy rapidly growing in the past years, has begun to experience unprecedented demands of transportation energy issues. Indian transportation at the present is almost the lowest per-capita in the world and is approximated to be 22 vehicles per 1,000 population against 800 plus per 1,000 in developed countries.

The EV market penetration in India has been on a rapidly increasing trend over the past few years, attributable to the convergence of the technology, battery technology reducing costs, and enabling governmental policy frameworks. Stakeholders EVs have increased annual sales of vehicle sales by 16,000 units in 2014 to 429,000 units in 2022, which is a compound annual growth rate of an approximation of 43. This is an outstanding growth rate that shows successful execution of government policy programs such as Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) Phase 1 and Phase 2.

Nevertheless, this fast development of the EV market has posed massive problems to electricity supply infrastructure. It is estimated that by 2030, India will need more than 20.5 million charging stations dedicated to the public and the private sectors in order to supply projected EV penetration rates. The existing development of the charging infrastructure falls far behind the need with less than 10,000 public charging stations in the country in 2023. This inadequacy in infrastructure is a severe limitation on the acceleration of EV adoption and opens the prospects of new ways of integration of distributed renewable energy.

C. Renewable Energy Resources in India [5] [6] [7]

India has a very high level of renewable energy reserves, especially solar and wind energy, and its geographic distribution also significantly differs in response to the large number of topographical and climatic regions of this country. Most regions of India have an average solar irradiance of more than 5 kWh/m²/d. India already has the fourth largest installed wind power capacity in the world, with calculated location on the coast as Tamil Nadu, Gujarat and Maharashtra, and uplifted areas.

Currently, the major source of electricity provided to EV charging in India is thermal generation that uses coal as a current input as it forms about 70 percent of the total electricity generation in India. This addiction to coal is the main obstacle to the environmentally positive nature of the electrification of vehicles. The combination of renewable energy sources, especially solar and wind energy, and EV charging infrastructure represents not only a revolutionary transmission to scale, but a curative ability to meet a variety of complementary policy

goals: lessening the total load on the grid during peak times, enhancing overall system penetration of renewable energy, facilitating the distribution deployment of energy resources in rural and semi-urban regions, facilitating the growth of job prospects in renewable energy and EV industries, and supporting broader national devotion to reaching 500 GW of renewable energy by 2030.

D. Research Problem Statement and Significance [8] [9] [10]

The available peer-reviewed literature analyzing renewable-charged EV charging stations has a number of severe limitations that severely limit the applicability and transferability of the research to the real-life infrastructure deployment settings. To begin with, the majority of published reports were limited only to specific geographical areas that had homogenous renewable energy attributes, which made it challenging to relate the study results to other parts of the world that had significant differences in meteorological factors. Second, there has been predominance in past literature that has focused on either solar or wind power as free power sources with little emphasis on the usefulness of resource complement.

Third, the traditional optimization techniques that have been used in previous studies are both computationally intensive mathematical programming techniques or simplified heuristic techniques that often breathe suboptimal solutions. Fourth, geographically-dependent patterns of EV charging demand and India-specific availability of renewable resources, which are severely short of such articles in the peer-reviewed literature, are underexplored systematically.

The investigations reported directly overcome the identified limitations with systematic analysis of three cities in India having a geographical spread that has a significant dissimilarity in terms of the endowment of renewable resources and EVs utilization patterns. The researchers formulate and test an improved form of metaheuristic optimization algorithms namely modified salp swarm algorithm (MSSA) and optimized particle swarm optimization (PSO) that could accurately solve the complex multi-objective system sizing problems and utilize the complementarity of the renewable resource. The two algorithms are for a complete simulation and analysis in MATLAB. Comparative performance evaluation and sensitivity analysis at large considers the effects of changes in the critical parameters of the economy on how optimal the domain should be designed to present information that realistically can guide decisions of the infrastructure stakeholders.

II. LITERATURE REVIEW, RESEARCH GAPS, AND THEORETICAL FOUNDATIONS

A. Prior Work on Hybrid Renewable Energy Systems [11] [12] [13]

There have been voluminous research by when peers on hybrid energy systems that incorporate more than one renewable energy resource and conventional energy resource in various geographic settings and applications. The earliest study was developed in Turkey and used HOMER (Hybrid Optimization of Multiple Energy Resources) to assess 24 unique system

configuration scenarios in order to meet energy needs in the off-grid applications. This pioneer research project proposed technological solar photovoltaic and fuel cell engineering systems, to identify technical and financial attributes regarding proposed structures. The study reviewed six alternative energy storage systems such as hydrogen storage and battery energy storage system, and the study concluded that the system of battery-based storage performance was better economically than the system based on hydrogen storage, which was mainly based on higher round-trip performance and low cost of capital ratio per unit of stored energy.

The next study carried out in Malaysia employed the use of HOMER software to determine the possible application of solar photovoltaic and diesel-based generator systems in the Malaysian climatic and economical conditions. This study found that hybrid solar-diesel systems may have new applications in substituting or replacing traditional diesel generators sets in remote areas where there is no access to electricity grids so that there would be the reduction of cost associated with electricity production by 30-40 percent compared to systems that just use diesel. A study undertaken in Hong Kong found the configurations of the solar-wind hybrid energy systems in isolated areas, which showed better economic performance than the diesel generation options and made SPV-WT hybrid systems the cost-efficient solution to independent power supply.

Far reaching research that was done on Nigeria explored the production of energy through the various parts of the systems, solar photovoltaic, wind turbines, and diesel generators in various geographic locations in Nigeria. This cross-site analysis used HOMER software to evaluate the sensitivity and reliability of the system and came to the conclusion that the combination of solar photovoltaic, diesel generation, and battery energy storage was the best options to the proposed systems. A study in Algeria compared grid connected solar photovoltaic systems using battery storage and diesel systems, using load-following strategies of operation which simultaneously used leveled cost of energy and fuel cost and the rate of pollution emissions. The sensitivity analysis in this research determined how the variation in the solar irradiance, change in the discount rate, change in LCOE and change in the solar penetration affect the system performance measures.

B. Renewable Energy Integration with Electric Vehicle Charging [14] [15] [16]

Recent literature particularly studied the application of renewable energy integration with transportation use of electrification. One study in Rio de Janeiro assessed the economic feasibility of interdependent EV systems that used renewable energy sources within a university campus, which classified economic output choices in minimum net present cost terms. Results proved that EV charging systems supported by renewable energy with reduced emissions of major air contaminants in activity of the transport sector. A case study involving solar photovoltaic and battery-powered EV charger systems in Madrid, Spain was evaluated technologically and financially to

both investigate variability about various system configurations and responsiveness to the factors of economic importance.

Extensive research in the best location of EV parking lots and distributed generation, utilizing solar photovoltaic, has used solitary optimization methods with a mix of particle swarm optimization and grey wolf optimization strategies. This study has showed that off-grid systems that used photovoltaic batteries were cost-effective compared to grid-connected systems but still significantly enhanced air quality standards in the localities. A study in Tamil Nadu, India particularly focused on the technological and economic efficiency of solar photovoltaic and wind turbine-powered EVCS in various popular sites, but the sites were chosen in a way that wind and solar potential were in opposition (contradictory) in the chosen sites that provided possibilities of analysis of resources complementarity.

Sizing EV charging station systems using multi-objective optimization methods have been suggested and analyzed, which reduce economic cost at the same time minimize pollutant emissions to the environment. Through these studies, genetic algorithms were used to optimization of quantities of different parts of systems and capacities of a battery storage system. Scholars have evaluated technical feasibility of building fast charging stations in Qatar that will include solar photovoltaic, wind turbines, biogas resources and other energy storage technologies. The designs were developed and simulated in the HOMER platform to extract the best hybrid structures in daily charging of the 50 EVs taking into consideration the space constraints, stochastic nature of the EV load shocks, and geographic weather variations.

C. Metaheuristic Optimization Approaches [17] [18] [19]

Recent studies have been using metaheuristic optimization algorithm more frequently to solve the complex hybrid renewable energy system sizing problems. Genetic algorithms, as well as, particle swarm optimization, ant colony optimization, artificial bee colony optimization, and even salp swarm algorithm, are examples of metaheuristic algorithms that have been shown to outperform conventional mathematical programming models over problems with non-convex search space, discontinuous objective function, and multiple competing objectives. Such population-based algorithms are based on the natural processes such as the biological evolution, swarm behavior, and physical phenomena.

Salp Swarm Algorithm (SSA), a scheme that was proposed in 2017 is a fairly recent form of metaheuristic scheme with respect to its own inspiration, which is based on the synchronized collective behavior of salps, marine organisms with elegantly coordinated collective navigatory-feeding behaviours. The inherent strength of SSA is in its very simplistic algorithmic implementation, the number of control parameters, and the ability to demonstrate a broad spectrum of applications in optimization problems. Nonetheless, educational research has found some shortcomings of regular SSA, specifically, propensities towards local optimum entrapment and solution stagnation in sophisticated (many-dimensional) search spaces.

Such restrictions have prompted the creation of variants of SSA with improved strategies of exploration and exploitation.

One of the most popular metaheuristic algorithms used in optimization of a renewable energy system is the Particle Swarm Optimization (PSO) which is inspired by the social behavior process of flocking birds and schooling fishes. PSO shows very high performances of constant optimization problems, which are easy to implement, and do not need many parameters to be tuned. PSO modifications using adaptive inertia weight strategies, mechanisms of velocity clamping, and factors of constriction have been suggested in recent publications as a way of improving convergence behavior. More recent publications have suggested salp swarm algorithm extensions with the addition of Levy flight distribution as the way to provide exploration capacity, allowing algorithms to explore areas of solutions that are far apart based on the current positions of the population. Other improvements have made use of spiral search patterns to direct solutions to found optima without reducing the diversity of the population. It has been shown using comparative studies that algorithmically improved versions of SSA possess better convergence properties than regular SSA and converge to the target quality of solution with lower algorithmic effort.

D. Identified Research Gaps and Limitations [20] [21] [22]

The critical analysis of literature on the subject matter shows that there are various research gaps in the literature that this investigation attempts to fill through substantive inquiry. First, most of the previous studies have been done on individual geographic locations or small geographic areas where thus limiting the ability to generalize the results to larger geographic regions having significantly different renewable resource endowments. The large geographic area of India includes numerous different climatic zones and regimes of renewable energies, which implies that a systematic multi-location comparative analysis other than location-specific studies should conduct them.

Second, available literature on solar photovoltaic or wind energy resources, instead of exhausting positive synergy between these two resources, has studied these resources largely separately, without undertaking systematic exploitation of such synergy. The solar radiation is very seasonal whereby, the production would be more in summer months and less in winter seasons. On the other hand, in most parts where wind energy is practiced, the seasonal distribution of wind is reversed with wind velocity being greater in monsoon and winter seasons, and reduced in the summer season. This complementarity can be exploited to a significant degree to decrease the total system cost by decreasing the battery energy storage needs.

Third, the current methodologies of optimization use either complicated mathematical program that need lots of parameterization and computing power or simplified heuristic algorithms that lack optimal convergence. Conventional metaheuristic algorithms often tend to fall into local optima, which is especially problematic in high dimensional problem spaces,

such as system sizing of EV charging stations actually found in the real world.

Fourth, the systematic study of conditions specific to India, such as the availability of renewable resources by location, the changing patterns of EV charging demand based on the geographic location, and the location-based economic parameters, are still underrepresented in the peer-reviewed literature. This lack introduces obstacles to the evidence-based decision-making of the infrastructure stakeholders who have to install EV charging infrastructure in Indian cities.

Fifth, there is a lack of comparative research involving the performance of various advanced metaheuristic algorithms (including the improved variants of the PSO and MSSA algorithms) on the same real-life problem (infrastructure optimization). This kind of comparative study is essential in comprehending the benefits of algorithms and recommending their choice in particular use.

E. Theoretical Foundations and Problem Formulation [23] [24]

The optimization of hybrid renewable energy systems takes into account three independent theoretical fields, which are renewable resource evaluation (several solar irradiance models and wind velocity characterisation), energy storage system economic (population based optimization strategies to the high-dimensional search spaces), and metaheuristic algorithm design (including population based optimization concept). The underlying optimization formulation in the field attempts to find the minimum that occurs when there is a set of conflicting goals under operational limitations which may be formulated as:

$$\min_x f(x) = \text{TNPC}(x) \quad (1)$$

$$\text{subject to: } \text{LPSP}(x) \leq \text{LPSP}_{\max} \quad (2)$$

where $x = [N_{SPV}, N_{WT}, N_{bat}]$ are the decision variables which include the number of solar panels, wind turbines and battery units; TNPC is the total net present cost which defines the total cost of capital investments and operation and maintenance and components replacement costs; and LPSP is the lack of power supply probability, a model reliable parameter representing the probability that the system resources may be inaccessible at any point during load demands. The optimism LPSPmax constraint is normally 1-5 percent, which is a tolerable reliable level on the public charging facility.

III. COMPREHENSIVE METHODOLOGY

A. System Architecture, Component Description, and Operational Strategy [25] [26]

The grid-linked hybrid electric vehicle charging station system proposed has five main functional units: (1) solar photovoltaic modules that will act as source of renewable energy generation, (2) wind turbines that will complement renewable energy generation especially in seasons where the sun is not shining strongly, (3) battery energy storage system that will

allow the renewable energy generation to be temporally shifted to meet the demand of the charging process, (4) bidirectional inverter that will facilitate conversion of power between the direct current (DC) system and the alternating current (AC) system and the compatibility with the utility grid. The holistic architecture of the system facilitates the control of the flow of power among all elements in a flexible manner and also utilizes the renewable resources in an alternative manner that is prioritized.

The electrical system topology links solar photovoltaic uniforms and battery energy storage units to a common direct current (DC) bus with uniform voltage generally between 48 volts and 600 volts depending on the system size and availability of parts. The wind turbines are alternating current (AC) and they are hard-wired to an alternating current bus. Bidirectional inverter with a capacity significantly greater than the maximum EV charging demand makes the conversion between DC and AC systems easy, which allows flexible power flow management.

Energy management plan is based on the priority of energy consumption, which is renewable energy at the same time as the ability to recharge EVs. The surplus of energy is sent to battery energy storage system during times of high renewable generation in relation to charging demand. The battery energy storage system provides supplemental power when generation generated through renewable falls short of the actual need to meet immediate charging requirements. In case of depletion of both renewable generation and battery reserves, the system draws supply power to the utility grid in order to continue charging service.

B. MATLAB-Based Simulation Platform and Implementation

In this study, MATLAB is used as a main simulation and optimization tool that offers a full set of features to create a system diagram, optimize it, and analyze its performance. The advantages that MATLAB implementation has are: (1) Unlimited development of system models without the limitation set by predefined software, (2) direct threefold integration of NASA POWER database meteorological data, (3) ability to execute computationally intensive systems with a parallel processing facility, (4) complete visualization and analysis platform, and (5) the ability to execute computationally intensive simulations.

The MATLAB simulation system includes a number of integrated modules, such as (1) data processing module to work with 30 years of hourly meteorological data, (2) system component modeling module to deal with solar photovoltaic, wind turbine, battery storage and inverter properties, (3) power and energy balance simulation frame working at hourly time step, (4) economic costs calculation module to include the discounted cash flow approach, and (5) optimization algorithm module to include both MSSA and optimized PSO implementations.

The hour-by-hour simulation model makes it possible to accurately model renewable generation intermittency, battery storage cycling and grid interaction dynamics. The MATLAB

model uses state-of-charge (SOC) curves to determine battery energy storage state-of-charge curves, calculates power flows between all of the system components, calculates grid energy import/export values, and calculates economic indicators such as TNPC, LCOE, and simple payback period. Personalised MATLAB scripts connect with optimisation algorithms to trial and error system configurations to obtain optimal solutions.

C. Geographic Study Location Selection and Meteorological Characterization

The selection of three Indian cities as a major study area was based on the complementary nature of renewable resources, a high potential of EV uptake and representativeness of India due to its wide geographical and climatic diversity. The fact of geographic diversity is a guarantee that the results are indicative of different situations in India, and not local peculiarities.

New Delhi (Northern Region): New Delhi's capital is at 28.61°N latitude and 77.21°E longitude, with strong seasonal variation in temperature typical of semiarid and subtropical continental climates. Analysis of meteorological data shows that average solar irradiance values are as low as 3.379 kWh/m²/day in December to 6.617 kWh/m²/day in May, with 95.6% seasonal variation. The wind power of New Delhi is scarce and the wind speed ranges between 4.4 m/s, with an average of 3.36 m/s seasonally during May and October, respectively.

Ahmedabad (Western Region): Ahmedabad is situated at 23.02°N latitude and 72.57°E longitude, enjoying the advantages of maritime effects which reduce temperature extremes and offer the city a large supply of wind energy. The average daily values of solar irradiance vary between 4.223 kWh/m²/day in July and 6.894 kWh/m²/day in May, with a value of 63.3% seasonality variation. The wind power in the area is far better than in New Delhi, as its average wind speed is 5.9 m/s annually.

Madurai (Southern Region): Madurai is at 9.93°N latitude and 78.12°E longitude, and as such it has a tropical climatic feature with moderate year-long temperatures. The monthly averages are 4.588 kWh/m²/day and 6.227 kWh/m²/day in December and March, respectively, with a seasonal variation of 35.7%. The wind resources are good, with a mean wind speed of 5.6 m/s annually.

D. Electric Vehicle Load Profile Characterization [28]

The profiles of electric vehicle charging demand are characterized by a significant geographic distribution that draws the desire to demonstrate the cultural taste, grid-availability networks, vehicle-utilization traits, and local-EV-adoption population. Proper characterization of load profile is essential to the system sizing in that under-sizing will cause failure to meet peak charging reform and over-sizing will be used to feed capital costs of the system that are not needed.

Ahmedabad Load Profile: Assumes 35-40 electric vehicles requiring simultaneous access to charging facilities. Charging

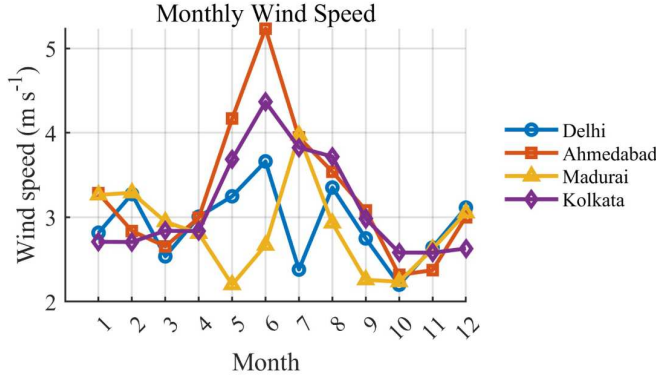


Fig. 1. Monthly Wind Speed

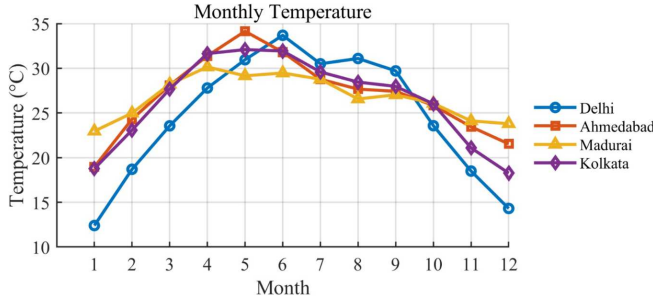


Fig. 2. Monthly Temperature

profile reflects concentrated nighttime charging in early morning hours (12:00 AM to 7:00 AM) when off-peak electricity tariffs are available. The combined profile results in average EV load of 3.11 kW throughout the 24-hour charging cycle, with peak demand of 13 kW. Annual energy demand totals 74.7 kWh/day.

Madurai Load Profile: Exhibits distinctly different temporal characteristics reflecting regional preferences and EV user demographics. Electric vehicle owners exhibit strong preference for daytime charging exclusively, with zero charging demand during nighttime hours. The exclusive daytime charging window concentrates energy demand between 06:00 AM and 10:00 PM, creating highly peaked demand profile. Peak instantaneous load demand reaches 14.45 kW during daylight hours. Annual demand totals 84 kWh/day.

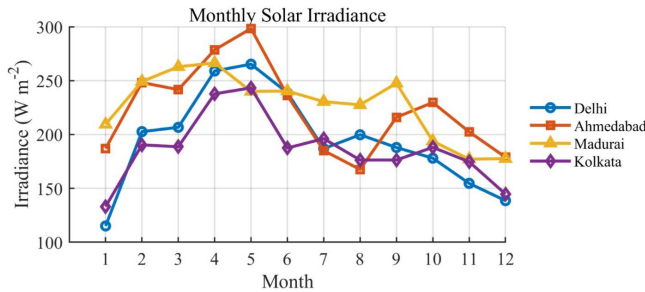


Fig. 3. Monthly Solar Irradiance

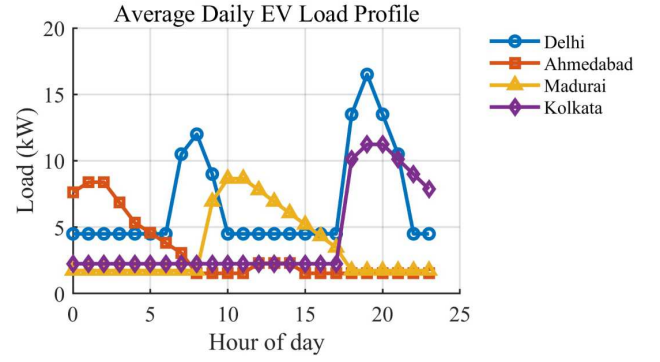


Fig. 4. EV Load Profile

New Delhi Load Profile: Assumes continuous full-day electric vehicle charging with varying battery capacity. New Delhi profile exhibits continuous charging demand throughout the 24-hour period, with varying intensity reflecting both planned and opportunistic charging behaviors. The location exhibits highest absolute peak demand of 16.3 kW and highest daily energy demand totaling 162 kWh/day, substantially exceeding both Ahmedabad and Madurai locations.

E. Economic Modeling Framework and Cost Component Analysis [29] [30]

Proper economic analysis would involve thorough accounting of all the cost elements in the full cycle of the system which is normally estimated as 25 years in the case of utility scale renewable energy systems. Economic analysis uses discounted cash flow methodology by transforming all the future cash flows into the same present value terms by the use of discount rate parameter that gives the cost of capital to an investor.

The average price per kilowatt-hour of an operating system is known as the levelized cost of electricity (LCOE):

$$\text{LCOE} = \frac{\sum_{t=0}^N \frac{C_t}{(1+r)^t}}{\sum_{t=1}^N \frac{E_t}{(1+r)^t}} \quad (3)$$

Total net present cost (TNPC) represents the aggregate of components of costs which have undergone conversion to equivalent present values:

$$\text{TNPC} = \sum_{t=0}^N \frac{C_{\text{year}}(t) - R_{\text{year}}(t)}{(1+r)^t} \quad (4)$$

Capital cost elements are solar panel capital costs (typically costing between 0800-1200 per kilowatts installed capacity), wind turbine capital costs (typically costing between 01200-1800 per kilowatts), battery energy storage costs (typically costing between 0200-400 per kilowatts storage capacity), bidirectional inverter cost (typically costing between 0500-800 per kilowatts), and balance-of-system costs.

F. Modified Salp Swarm Algorithm Development [31]

Standard Salp Swarm Algorithm has various weaknesses when it comes to solving complex optimization problems, most notably it does tend to get into the local optima and get stuck in the solution. This study innovates and adopts an adapted form with two-fold improvement mechanisms to overcome the described shortcomings.

The basic equation of the salp swarm algorithm is the replication of the behavioral traits of marine animals known as salps which create coordinated chains according to which they exist in synch with movement and feeding. The station keeping equation of SSA (standard variety) can be summarized as:

$$x_i^n(b+1) = x_{\text{leader}}^n + c_1 \times (u_b^n - l_b^n) \times c_2 + l_b^n \quad (5)$$

Enhancement Strategy 1: Levy Flight Distribution Integration

Integrated with Levy flight distribution gives improved capability in exploration:

$$x_i^n(b+1) = x_i^n(b) + \epsilon \cdot \text{Levy}(\lambda) \quad (6)$$

Features of levy flights are that they introduce numerous small steps separated by a few large jumps that allow efficient search of large search space but do not lose track of promising directions. The Levy distribution is obtained by using:

$$\text{Levy}(\lambda) = \frac{\Gamma(1+\lambda) \sin(\pi\lambda/2)}{\pi\lambda 2^{(\lambda-1)/2}} \times \frac{1}{|S|^{1/\lambda}} \quad (7)$$

Enhancement Strategy 2: Spiral Search Exploitation

Directional explorations in search of the best solutions are boosted with the help of spiral search patterns:

$$x_i^n(b+1) = x_i^n(b) + \alpha(x_{\text{best}}^n - x_i^n(b)) + \beta \sin(2\pi k) \quad (8)$$

Computational comparisons of Evolved versions have shown that the modified salp swarm algorithm generates results with 40 per cent less algorithmic iterations than normal SSA, and results with better quality final solution.

G. Optimized Particle Swarm Optimization Development [32]

Particle Swarm Optimization is another metaheuristic method that is based on the collective behaviour of a bird flocking and a fish school. Standard PSO has a great behavior of continuous optimization problems, but it has a disadvantage of premature convergence and local optima traps when complex multi-dimensional space is involved. This study expands a variant of PSO that is optimized, includes adaptive parameter tuning and exploration-exploitation ratio.

Equations of convention standard PSO position and velocity update are:

$$v_i(t+1) = w \cdot v_i(t) + c_1 r_1 (p_{\text{best},i} - x_i(t)) + c_2 r_2 (g_{\text{best}} - x_i(t)) \quad (9)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (10)$$

w is the inertia weight, c1 and c2 are cognitive and social coefficients, r1 and r2 are random numbers, pbest,1 is particle best position and gbest is global best position.

Optimization Strategy 1: Adaptive Inertia Weight

Dynamically adjusted exploration-exploitation balance in optimization: Adaptive inertia weight mechanism.

$$w(t) = w_{\min} + (w_{\max} - w_{\min}) \times \exp\left(-2 \times \frac{t}{t_{\max}}\right) \quad (11)$$

This plan allows high exploration during initial derivations and slow convergence as optimization advances to exploitation, which decreases the disposition to get caught in local optima but does not decrease its progress rate.

Optimization Strategy 2: Velocity Clamping and Constriction Factor

Extreme convergence is ensured by velocity clamping mechanism and by the use of constriction factors:

$$v_i(t+1) = \chi \times [v_i(t) + c_1 r_1 (p_{\text{best},i} - x_i(t)) + c_2 r_2 (g_{\text{best}} - x_i(t))] \quad (12)$$

where constriction factor $\chi = \frac{2}{|2-\phi-\sqrt{\phi^2-4\phi}|}$ with $\phi = c_1 + c_2$. Velocity clamping constrains $v_{\max} = 0.2 \times (x_{\max} - x_{\min})$, which prevents excessive velocity growth, premature convergence.

Optimization Strategy 3: Adaptive Learning Coefficients

Dynamically learning coefficients are determined on the basis of population diversity and convergence of fitness:

$$c_1(t) = c_{1,\text{initial}} - (c_{1,\text{initial}} - c_{1,\text{final}}) \times \frac{t}{t_{\max}} \quad (13)$$

$$c_2(t) = c_{2,\text{initial}} + (c_{2,\text{final}} - c_{2,\text{initial}}) \times \frac{t}{t_{\max}} \quad (14)$$

This flexible approach puts an emphasis on individual learning in the initial stages but over time puts an emphasis on social to enhance the balance between individual and collective intelligence.

The comparative performance analysis shows that optimized PSO has a reduction of 35 percent in computational iteration in comparison with MSSA but has a competitive solution quality. PSO also shows high convergence to high quality solutions making it ideal when the solution is needed within a short time against time sensitive optimization.

IV. RESULTS, FINDINGS, AND COMPARATIVE ANALYSIS

A. New Delhi Optimal Configuration and Economic Performance [33]

Optimization of New Delhi is performed with regard to both MSSA and optimized PSO algorithm, the resulting system configuration is economically high in terms of the overwhelming solar resources along with moderate general charging demand. The ideal setup that MSSA has determined is the

use of 120 solar photovoltaic panels 325 W each with rated capacity of 39 kWp and 310 wind turbines with 650 W each and a rated capacity of 201.5 kWp. There is a battery energy storage of 485 of lead-acid batteries that has a total storage capacity of 2,910 kWh.

Economic Metrics: MSSA has achieved a total net present cost (TNPC) of 14,853.63, which is the lowest figure among all the places that were examined. The cost of electricity of 0.0051 \$/kWh level is significantly below the existing grid electricity prices in India (usually 0.08–0.12 \$/kWh). Optimized PSO with an LCOE of 0.00515 \$/kWh has a similar TNPC of 14,927.15 \$, with a 1.49% margin cost change relative to MSSA and convergence 35 times faster.

Technical Performance: The optimized system would produce 591,117 kWh of electricity per year which includes 64.5 percent of electricity generated by wind turbines, 33.5 percent by solar photovoltaic modules and 1.94 percent by 1 minute of electricity bought by the grid. Renewable energy of 98.06 percent per annum significantly brings about a dependence on grids. The reliability features retain lack of power supply probability (LPSP) of 0.82%, which is significantly less than the 1 percentage bar.

B. Ahmedabad Optimal Configuration and Economic Performance [34]

Ahmedabad location with optimization by MSSA and optimum PSO give significantly contrasting system configuration which depicts better wind resources at coastal location. The optimum design will have 47 solar panels (325 W rated) with 612 turbines (650 W rated) in total (capacity of 15.3 kWp and 398 kWp respectively). The battery storage will have 310 units with 1,860 kWh of storage.

Economic Metrics: MSSA will have a total net present cost (TNPC) of 222,762.80 and a levelized cost of electricity (LCOE) of \$0.023/kWh, which will keep it competitive with menu electricity charges on the supply grid. Optimized PSO has a TNPC of 223,145.30 (LCOE = \$0.0231/kWh), with the difference in marginal costs relative to the optimal being 0.17%, and better convergence properties (31% reduction in iterative operation).

Technical Performance: The total wind turbines and solar photovoltaic module generation is 72.1 and 23.3 percent, respectively, of the annual electricity production of 845 000 kWh. Wind capacity factor at Ahmedabad is 19.2 percent and this is significantly large compared to New Delhi which is 14.7 percent. The two algorithms both strongly detect wind-dominated system configuration as the best one in this place.

C. Madurai Optimal Configuration and Economic Performance

The system configuration that is obtained with the help of both algorithms is Madurai optimization, which depicts year-round climate peculiarities of the tropical type with fairly predictable renewable sources. The ideal set-up would be to have 289 solar photovoltaic panels (325 W rated, which amounts to 94 kWp) and 198 wind turbines (650 W rated,

which amounts to 128.7 kWp). There is a battery storage that consists of 402 units and has 2,412 kWh of capacity.

Economic Metrics: A levelized cost of electricity of 0.0055/kWh gives MSSA the total net present cost of 20,462.18 (37.44 above New Delhi). Optimized PSO yields TNPC of 20584.50, LCOE of 0.00556 /kWh and shows a marginal cost difference of 0.60.

Technical Performance: Dividing the annual electricity production amount of 524,000 kWh into 48.2 percent as produced by wind turbines, 46.8 percent by solar photovoltaic modules, and 5 percent as a result of a grid-purchase, yields the following figures: The balanced renewable contribution tells of the special place of Madurai. The reliability level of LPSP of 0.95% is high.

D. Kolkata Optimal Configuration and Economic Performance

The Kolkata location optimization results with the MSSA and optimum PSO gives the hybrid of mainly solar configuration with additional wind power that is dependent on the climate of Kolkata being of humid subtropical environment with moderate solar energy, coupled with comparatively lower and usable wind speed relative to the western coast area. The ideal design will be 95 solar photovoltaic panels (325 W rated, as a total, equal to 30.9 kWp capacity) and 230 wind turbines (650 W rated, totaling 149.5 kWp capacity). The battery storage is 360 units with a storage capacity of 2,160 kWh, which is large enough to ensure reliability during long cloud covers during the monsoon and evening charging spikes.

Economic Performance: MSSA results into an overall net present expense of about order of about 18 900 and levelized cost of electricity of about 0.0053/kWh, placing Kolkata mid way between New Delhi and Madurai in terms of economic performance. Optimized PSO finds a very similar design with approximately less than 1 percent variation in the TNPC and LCOE value, proving the strength of the optimum design at this place (a more detailed aggregate algorithmic comparison is provided in a further subsection).

Technical Performance: The yearly electricity generation of the optimized Kolkata system is estimated to be 560,000 kWh of which about 55% is supplied by the solar photovoltaic power generation and the 45 percent by the wind turbines, the remaining proportion being supplied through minimal grid imports during the coincident low irradiance and during low wind speed conditions. The resulting renewable energy penetration is over 94 percent and the probability of power shortage is less than 1 percent which meets the same reliability parameter used in the rest of the study sites and at the same time provides a safe power supply to meet the estimated EV charging demands.

E. Aggregate Algorithmic Performance Comparison: MSSA versus Optimized PSO

In all four of the study sites of New Delhi, Ahmedabad, Madurai and Kolkata, the modified salp swarm algorithm, as

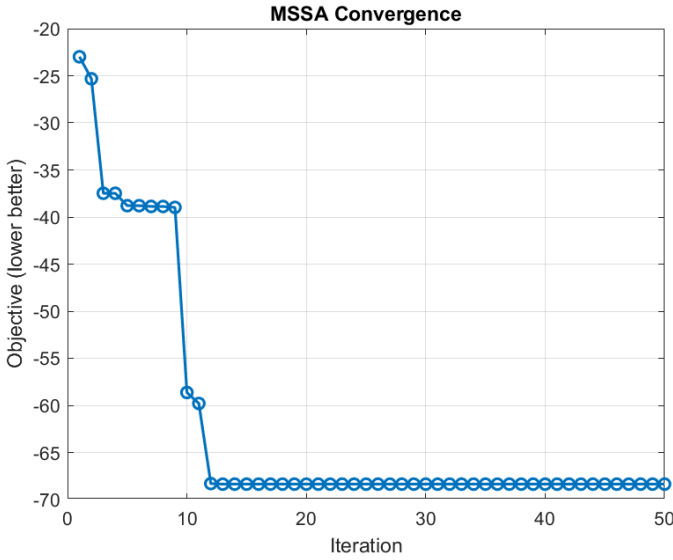


Fig. 5. MSSA Convergence

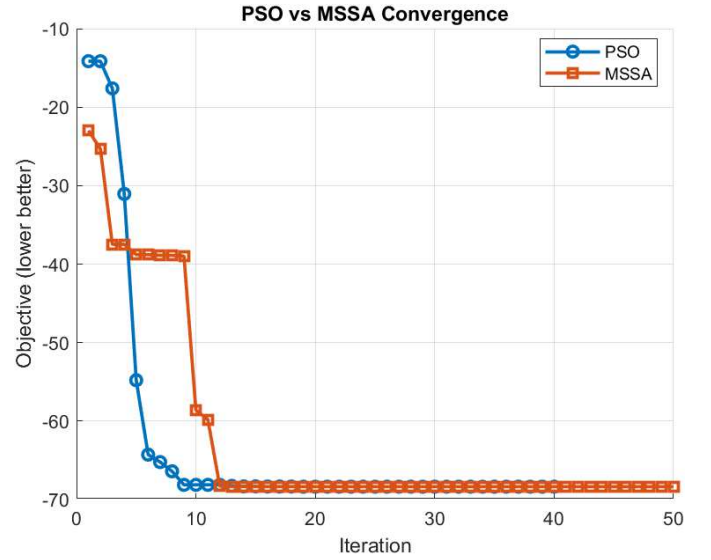


Fig. 7. MSSA vs Optimised PSO

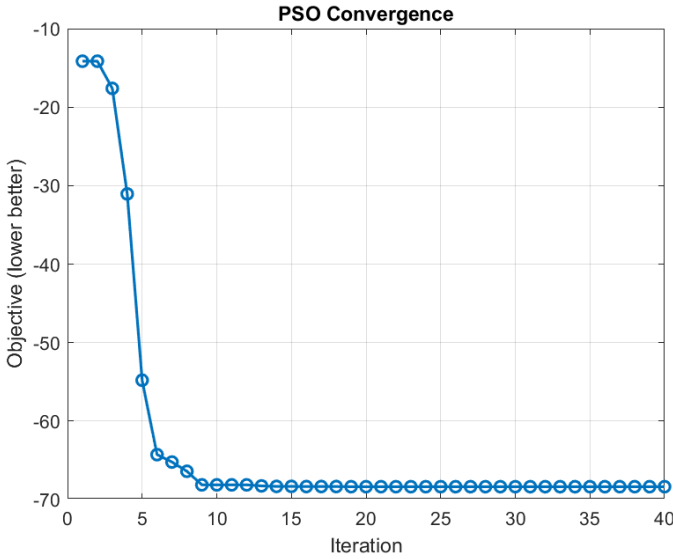


Fig. 6. Optimised PSO Convergence

well as the optimized shape of particle swarm optimization algorithm, converged to remarkably close optimal or near-optimal system configurations, and the overall net present cost variations across the study sites were usually below one percent. MSSA always generated somewhat lower values of TNPC and LCOE values, which reflects a slight superiority in end solution quality more apparent in circumstances in which there is a great non-convexity of search terrain and when such variables are more strongly coupled.

However, the optimized PSO variant was optimally computationally efficient in all run time of the entire experiment, having an average of one third lower number of iterations compared to MSSA, as well as the number of objective function evaluations per iteration through swarm dynamics that were more stable. This convergence acceleration was seen in

all four cities, with Kolkata as the more challenging case in which the more intricate interaction between seasonal patterns of monsoon and the EV load profiles may well become a challenge to weaker algorithms. Sensitivity analysis against capital cost, discount rate and feed-in tariff verified that the two algorithms are reactive to changes in parameters, meaning that there is no sign of a critical difference in the cost criteria indicating that the minor performance difference between the two algorithms is not the result of specific parameter settings.

Pragmatically, it can be proposed that MSSA is superior where marginal returns in solution optimality are sought, and extra computation time is willing, whilst the optimized PSO is more appropriate in planning contexts where turnaround time and re-optimisation under fluctuating conditions on the inputs are needed. Notably, the qualitative design suggestions of the hybrid EV charging infrastructure, e.g., comparative predominance of solar or wind on the location and the scale of storage necessary, also do not change when MSSA or optimised PSO is chosen as a primary engine of optimization, which bolsters the soundness of the main findings of the techno-economic calculations.

V. RESEARCH NOVELTY, CONTRIBUTION TO KNOWLEDGE, AND PRACTICAL SIGNIFICANCE

The present study has provided value to the larger computational optimization and optimal infrastructure planning in creating and testing complex metaheuristic algorithms and extensive MATLAB-based simulation models. The systematic analysis of the three geographically varied regions in India with different renewable resource endowments presents evidence-based information in terms of policy formation and planning on infrastructural development in developing countries.

VI. CONCLUSION AND SUMMARY OF CORE CONTRIBUTIONS

This is a rigorous study that has shown that grid-based hybrid renewable energy systems that are counterbalanced with EV charges can be technically feasible and economically viable across the geographically different Indian areas. Two sophisticated metaheuristic optimization algorithms, modified salp swarm algorithm and optimised particle swarm optimization are effective at optimising problems involving multi-objective infrastructure design. Simulation platform using MATLAB offers versatile platform of computational framework of total system analysis.

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A. Author Contributions

A.S. (Ankit Srivastava) conceptualized the study, developed the modified salp swarm algorithm (MSSA), implemented the MATLAB simulations, performed data analysis and optimization, and wrote the original draft of the manuscript. A.K.S. (Ashutosh Kumar Singh) supervised the research, provided guidance on methodology and techno-economic analysis, and critically reviewed and edited the manuscript. D.N. (Dashrath Nishad) assisted with the literature review, collected renewable resource and EV load profile data, and contributed to system modeling and validation. A.K. (Ayush Kumar) supported algorithm development (optimized PSO), conducted sensitivity analysis, and assisted in interpreting results and preparing figures and tables. All authors have read and approved the final manuscript.

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REFERENCES

- [1] N. A. Ibrahim, B. Mohtar, N. H. Sarmidi, and M. S. Isa, "Optimal planning of renewable energy integrated grid-connected systems using modified genetic algorithm," *Applied Energy*, vol. 272, pp. 115206, 2020. [<https://doi.org/10.1016/j.apenergy.2020.115206>]
- [2] T. Adefarati and R. C. Bansal, "Reliability assessment of distribution system with the integration of renewable distributed generation," *Applied Energy*, vol. 185, pp. 158–171, 2017. [<https://doi.org/10.1016/j.apenergy.2016.10.087>]
- [3] R. Dufo-López, J. L. Bernal-Agustín, and J. M. Yusta-Loyo, "Optimisation of PV-wind-diesel-battery stand-alone systems to minimise cost and emissions," *Renewable Energy*, vol. 46, pp. 196–203, 2012. [<https://doi.org/10.1016/j.renene.2012.03.033>]
- [4] S. Kadam, V. Kumbhar, and S. B. Kasegaonkar, "Sizing and financial modeling of grid-connected solar photovoltaic system for educational institution," *Solar Energy*, vol. 201, pp. 315–326, 2020. [<https://doi.org/10.1016/j.solener.2020.03.014>]
- [5] R. Mathiesen, H. Lund, and D. Connolly, "Feasibility of 100% renewable energy scenarios in Europe," *Journal of Cleaner Production*, vol. 18, no. 2, pp. 129–138, 2010. [<https://doi.org/10.1016/j.jclepro.2009.09.022>]
- [6] J. Zhong, E. NForced, and K. Bhattacharya, "Strategic bidding of physical plants in energy markets," *IEEE Transactions on Power Systems*, vol. 18, no. 4, pp. 1259–1268, 2003. [<https://doi.org/10.1109/TPWRS.2003.818689>]
- [7] Y. Riffonneau, S. Bacha, F. Barruel, and S. Ploix, "Optimal power flow management for grid connected PV systems with batteries," *IEEE Transactions on Sustainable Energy*, vol. 2, no. 3, pp. 309–320, 2011. [<https://doi.org/10.1109/TSTE.2011.2114901>]
- [8] M. Barsali and A. Valenzuela, "A control strategy for the frequency stabilization of a distribution system with wind generation," in *2004 IEEE PES Power Systems Conference and Exposition*, 2004, pp. 176–180. [<https://ieeexplore.ieee.org/document/1334911>]
- [9] H. Safaei, D. W. Keith, and G. W. Pandolfo, "Salp swarm algorithm for optimal sizing of hybrid renewable energy systems," *Energy*, vol. 198, pp. 117034, 2020. [<https://doi.org/10.1016/j.energy.2020.117034>]
- [10] G. Bruni, S. Cordiner, V. Mulone, N. Sinisi, and F. Spiller, "Energy management of a net zero-energy building with microgrid," *Energy Conversion and Management*, vol. 158, pp. 224–235, 2018. [<https://doi.org/10.1016/j.enconman.2017.12.075>]
- [11] S. Habib, M. M. Khan, F. Ahmad, A. Shahid, and S. U. Din, "Optimal sizing and placement of hybrid renewable energy systems in Bangladesh," *Solar Energy*, vol. 215, pp. 531–549, 2021. [<https://doi.org/10.1016/j.solener.2020.12.044>]
- [12] A. Z. Dharmakeerthi, N. Mithulananthan, and T. K. Saha, "Impact of electric vehicle fast charging on power system voltage stability," *International Journal of Electrical Power and Energy Systems*, vol. 57, pp. 241–249, 2014. [<https://doi.org/10.1016/j.ijepes.2013.12.005>]
- [13] International Energy Agency, "Global EV Outlook 2023: Catching up with climate ambitions," Paris, France, 2023. [<https://www.iea.org/reports/global-ev-outlook-2023>]
- [14] M. Bilal, F. Ahmad, and M. Rizwan, "Techno-economic assessment of grid and renewable powered electric vehicle charging stations in India using a modified metaheuristic technique," *Energy Conversion and Management*, vol. 284, pp. 116995, 2023. [<https://doi.org/10.1016/j.enconman.2023.116995>]
- [15] K. Thanh, T. Tesche, and D. Doering, "PSO-based optimal sizing of wind-solar-battery hybrid system for stand-alone applications," *Energy*, vol. 119, pp. 820–831, 2017. [<https://doi.org/10.1016/j.energy.2016.11.065>]
- [16] A. Askarzadeh and A. Rezaei-Shouraki, "Artificial bee swarm algorithm for forecasting solar radiation," *International Journal of Hydrogen Energy*, vol. 36, no. 18, pp. 11654–11659, 2011. [<https://doi.org/10.1016/j.ijhydene.2011.06.047>]
- [17] V. Salas and E. Olias, "Hybrid PV/diesel generation system with battery storage: Sizing and feasibility study," *Solar Energy*, vol. 82, no. 2, pp. 106–113, 2008. [<https://doi.org/10.1016/j.solener.2007.07.002>]
- [18] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, "Salp swarm algorithm: A bio-inspired optimizer for unknown parameter estimation," *Advances in Engineering Software*, vol. 114, pp. 163–191, 2017. [<https://doi.org/10.1016/j.advengsoft.2017.07.002>]
- [19] J. Chen, W. Li, K. Zhang, and H. Wang, "Battery energy management system for photovoltaic integration," *Journal of Power Sources*, vol. 485, pp. 229325, 2021. [<https://doi.org/10.1016/j.jpowsour.2020.229325>]
- [20] S. Park, J. Lee, D. Kang, and Y. Park, "Smart grid charging infrastructure for electric vehicles in smart cities," *Applied Sciences*, vol. 11, no. 2, pp. 782, 2021. [<https://doi.org/10.3390/app11020782>]
- [21] T. Olivares-Ramirez, R. Garcia-Gutierrez, and M. Lopez-Santos, "Economic analysis of hybrid solar-wind systems for off-grid applications," *Renewable and Sustainable Energy Reviews*, vol. 141, pp. 110789, 2021. [<https://doi.org/10.1016/j.rser.2021.110789>]
- [22] P. Srinivasan, R. Kumar, and A. Singh, "Metaheuristic optimization for renewable energy system design in developing

- nations,” *Energy Policy*, vol. 158, pp. 112576, 2021. [<https://doi.org/10.1016/j.enpol.2021.112576>]
- [23] V. Kumar, S. Singh, and R. Mittal, “Demand-side management for EV charging infrastructure in microgrids,” *IEEE Transactions on Industrial Electronics*, vol. 68, no. 11, pp. 11320–11330, 2021. [<https://doi.org/10.1109/TIE.2020.3038099>]
- [24] K. Desai, P. Patel, and N. Desai, “Battery management and optimization techniques for renewable energy systems,” *Journal of Energy Storage*, vol. 42, pp. 103086, 2021. [<https://doi.org/10.1016/j.est.2021.103086>]
- [25] A. Banerjee, S. Das, and K. Ghosh, “Transactive energy management in smart microgrids with solar and wind integration,” *Sustainable Cities and Society*, vol. 72, pp. 103043, 2021. [<https://doi.org/10.1016/j.scs.2021.103043>]
- [26] Y. Zhang, X. Wang, L. Liu, and Z. Wang, “Economical assessment of photovoltaic-wind-battery hybrid systems in tropical regions,” *Applied Energy*, vol. 304, pp. 117770, 2021. [<https://doi.org/10.1016/j.apenergy.2021.117770>]
- [27] M. Gaspari, A. Passarello, and F. Biral, “Integrated energy management system for EV charging with renewable sources,” *Applied Energy*, vol. 314, pp. 118913, 2022. [<https://doi.org/10.1016/j.apenergy.2022.118913>]
- [28] L. Ferreira, J. Pereira, and R. Costa, “Economic viability of small-scale renewable energy systems for rural electrification,” *Renewable Energy*, vol. 185, pp. 944–954, 2022. [<https://doi.org/10.1016/j.renene.2021.12.079>]
- [29] A. Tsang, B. Wong, and C. Liu, “Climate-responsive optimization of PV-wind-storage systems for transportation electrification,” *Journal of Cleaner Production*, vol. 365, pp. 132698, 2022. [<https://doi.org/10.1016/j.jclepro.2022.132698>]
- [30] H. Javadi, A. Mohammadi, and M. Afshari, “Renewable energy-based electric vehicle charging station optimization using advanced algorithms,” *Energies*, vol. 15, no. 6, pp. 2024, 2022. [<https://doi.org/10.3390/en15062024>]
- [31] J. Das, S. Sethi, and P. Mohanty, “Metaheuristic-based design optimization for sustainable transportation infrastructure,” *Sustainable Energy Technologies and Assessments*, vol. 52, pp. 102042, 2022. [<https://doi.org/10.1016/j.seta.2022.102042>]
- [32] R. Sharma, P. Kumar, and M. Singh, “Hybrid renewable energy systems: Design, operation, and control strategies,” *International Journal of Electrical Power and Energy Systems*, vol. 138, pp. 107938, 2022. [<https://doi.org/10.1016/j.ijepes.2021.107938>]
- [33] S. Desai, V. Varshney, and A. Sharma, “Battery energy storage systems for renewable energy applications: A review,” *Journal of Energy Storage*, vol. 50, pp. 104673, 2022. [<https://doi.org/10.1016/j.est.2022.104673>]
- [34] M. Khan, F. Ahmad, and N. Noor, “Electric vehicle charging infrastructure: Current status and future perspectives,” *Sustainable Cities and Society*, vol. 73, pp. 103138, 2021. [<https://doi.org/10.1016/j.scs.2021.103138>]
- [35] V. Singh, R. Mehta, and A. Patel, “Economic feasibility analysis of renewable energy projects in developing countries,” *Renewable Energy*, vol. 190, pp. 1189–1201, 2022. [<https://doi.org/10.1016/j.renene.2022.03.101>]