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Nature-Inspired Algorithms for Energy Management Systems:
A Review

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ABSTRACT

The electric grid is being increasingly integrated with renewable energy sources whose output is mostly fluctuating in nature. The load demand is also increasing day by day, mainly due to the increased interest in electric vehicles and other automated devices. An energy management system helps in maintaining the balance between the available generation and the load demand and thus optimizes the energy usage. It also helps in reducing the peak load, green-house gas emissions, and the operational cost. Energy management can be performed at different levels and is essential for realizing smart homes, smart buildings, and even smart grid. The different objectives considered for designing energy management systems are reduction of emissions, energy cost, operational cost, peak demand, etc. Many traditional and hybrid nature-inspired algorithms are used for optimizing these various objectives. This paper intends to give an overview about the various nature-inspired algorithms used for optimizing energy management systems in homes, buildings, and micro grid.

KEYWORDS

Energy Management, Nature-Inspired Algorithm, Optimization, Smart Building, Smart Grid, Smart Home

1. INTRODUCTION

Nowadays, there is a paradigm shift in the energy sector to meet the increased demand for continuous, secure, reliable and quality electric power. The transformation of traditional grid to a self- healing smart grid involves the integration of intelligent monitoring, control and communication technologies. This helps in promoting the increased integration of renewable energy based DG sources and electric vehicles resulting in reduced green-house gas emissions leading to sustainable energy environment. Energy management systems (EMS) optimize the energy usage with the help of advanced technologies for measurement, monitoring and analysis of data at homes, buildings and even at grid. Uncertainty due to the intermittent nature of renewable energy sources and the loads can be taken care of using EMS. The major objective of EMS is reduction in energy consumption leading to cost minimization.

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It also helps in managing the energy storage systems based on the renewable energy output. To meet the supply demand balance, flexibility at the load end can be effected with the help of demand response programs through EMS. Micro grid energy management systems can also be realized by implementing DSM using various pricing mechanisms (Shen et al., 2016). Figure 1 depicts the components involved in an energy management system.

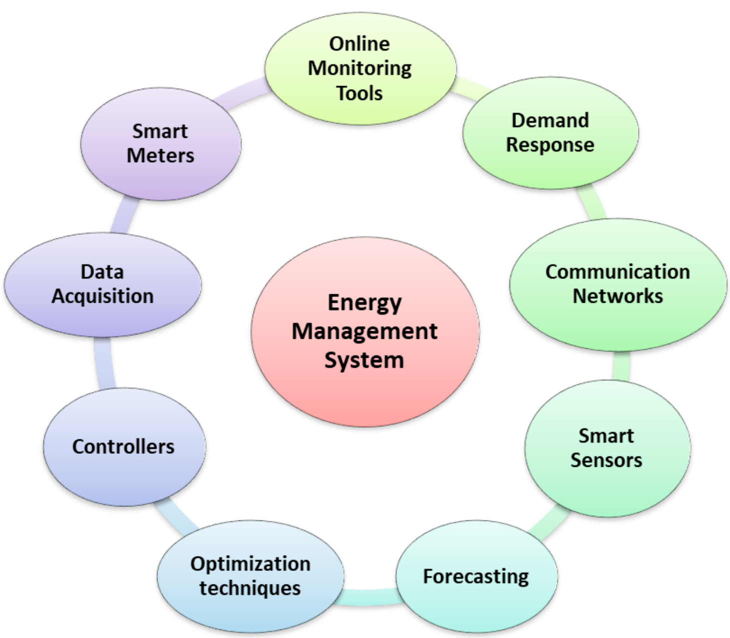
Based on the methodology used to achieve the objectives, EMS can be broadly classified into (i) Rule based; (ii) Optimization based and (iii) Learning based EMS (Tran et al., 2020). Rule based EMS optimizes the energy usage on the basis of a set of rules in accordance with an algorithm or fuzzy logic. Optimization based EMS employs classical or metaheuristic algorithms to achieve the objectives under a set of constraints. Learning based EMS uses the historical data for training the system with the help of machine learning and artificial intelligence techniques.

In this paper, the various nature inspired algorithms used by Optimization based EMS are discussed. The application of these algorithms to optimize energy usage in residential homes, buildings and in a smart grid is discussed. The various objectives considered along with the constraints are explained in detail. The most commonly used algorithms include Particle Swarm Optimization, Genetic Algorithm, Ant Colony Optimization, Bat Algorithm, Cuckoo Search Algorithm, Artificial Bee Colony Algorithm etc. In order to reap the benefits of different algorithms, few authors have optimized the objectives of EMS using hybrid algorithms as well. Recently developed algorithms like Dragonfly Algorithm, Wind-Driven Optimization, Grasshopper Optimization Algorithm, Moth Flame Optimization etc. are also being used for developing efficient, effective EMS.

2. PROBLEM FORMULATION

The objectives considered for realizing EMS are manifold in different contexts. Minimization of cost, energy consumption, emissions, frequency of interruptions, losses, peak to average ratio (PAR), electricity bill etc. and maximization of user comfort, reliability, grid sustainability, income etc. are

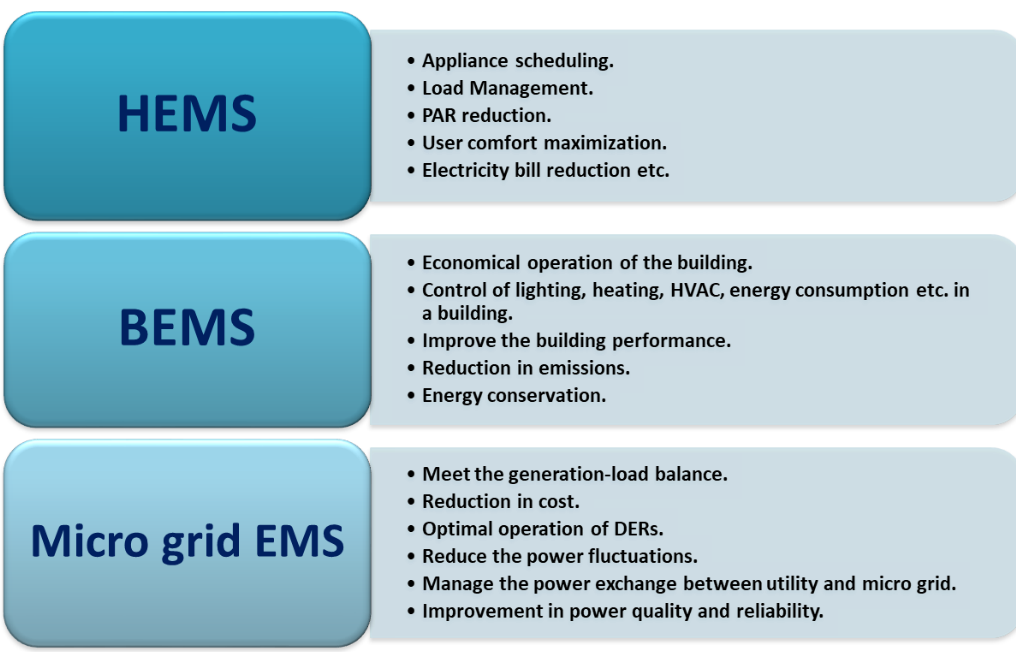
Figure 1.
Components of an Energy Management System



few of the most common objectives considered by different authors. Certain authors have considered multiple objectives, mostly by combining different single objectives using the weighted sum method. The constraints taken for the optimization problem include technical, economical, operational and other system constraints. Figure 2 represents the objectives involved in the Energy Management System in homes, buildings and microgrid Ahmad et al. (2017) proposed home energy management system (HEMS) which reduces the electricity bill and PAR by optimally scheduling the home appliances and energy storage systems (ESS) with the help of demand side management (DSM).

The electricity bill is reduced considering the dynamic pricing of electricity in the market and the reduction in PAR helps the utility and the customer to maintain the supply demand balance. The constraints include the operational constraints of the devices and their energy usage pattern. A smart micro grid energy management system (Singh et al., 2017) helps to minimize the total cost consisting of the start-up, fuel, operation and maintenance costs of the microgrid integrated with micro turbine, fuel cells, distributed generators, batteries and plug in hybrid electric vehicles (PHEV). The objective function is optimized under a set of constraints, which include DG, battery, PHEV capacity limits, grid and operating reserve constraints and the supply demand balance constraints. A two level EMS can also be used in a smart micro grid (Haseeb et al., 2020), one at the home level to minimize the cost and optimally utilize the resources, the second level EMS for enabling energy trading between the smart homes. Apart from cost minimization and PAR reduction, user comfort enhancement (Mouassa et al., 2021) is also included along with the objective function for HEMS. User comfort is maximized by reducing the waiting time experienced by the customer during device scheduling. Reduction in the greenhouse gas emissions (Imran et al., 2020) is taken as one of the objectives for EMS in residential homes. Energy management in a distribution network (Azizivahed et al., 2018) is done by considering multiple objectives like reduction in operation cost and reliability improvement. Reliability is quantified by evaluating the energy not supplied (ENS) index and the solutions are obtained by analyzing the Pareto optimal front. The constraints considered are the power balance equations, the line capacity limits, the voltage limits and the battery constraints.

Figure 2.
Energy Management System in homes, buildings and microgrid



3. NATURE INSPIRED ALGORITHMS FOR EMS

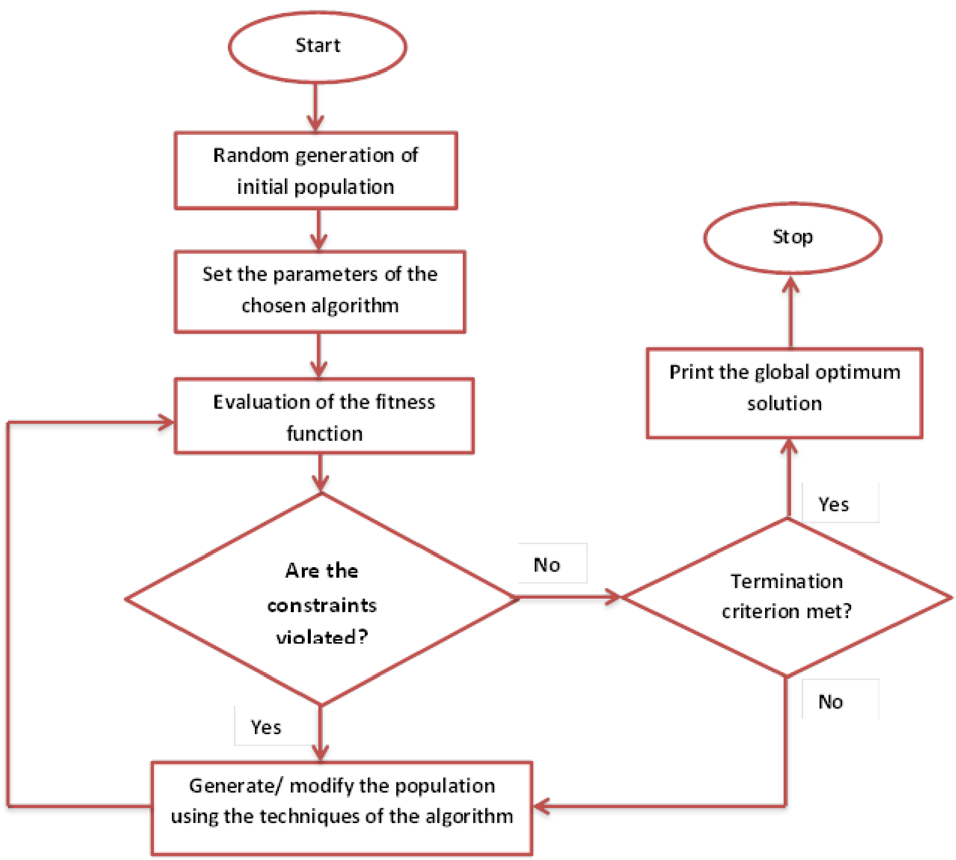
Recent years have seen a tremendous increase in the use of nature inspired algorithms for solving complex optimization problems. They are formulated based on the various phenomena / processes occurring in nature. Compared to the traditional or classical optimization algorithms, the nature inspired algorithms which have the stochastic components works far better due to the consideration of randomness in generating the solution set which increases the exploration ability. A few of the commonly used algorithms used for optimizing the performance of energy management systems are detailed below.

The general flowchart of the processes involved in the optimization algorithm is shown in Fig.3.

3.1 Particle Swarm Optimization (PSO)

A PSO is a population based heuristic methodology that imitates the behaviour of flock of birds or a school of fishes. The technique is developed by Dr. Eberhart and Dr. Kennedy in 1995. PSO uses many particles which are part of a swarm moving around in search of the best solution. PSO is an iterative process in which each particle position itself according to its own experience (P_{best}) and according to the neighboring particles experience (G_{best}). The optimal search process continues until a relatively optimal position is reached. The optimal solution is validated by the total number of loops completed or in accordance with the convergence characteristics. The particles' velocity and position are updated in every iteration based on the expressions given in equation (1) and (2).

Figure 3. Flowchart of an optimization algorithm



$$V_{i+1} = \omega * V_i + C_1 * rand * \left(P_{best} - X_i\right) + C_2 * rand * \left(G_{best} - X_i\right) \tag{1}$$

$$X_{i+1} = X_i + V_{i+1} \tag{2}$$

where, X_i and X_{i+1} are the position of the particle during the i^{th} iteration and $(i+1)^{th}$ iteration, V_i and V_{i+1} are the velocity of the particle corresponding to the i^{th} iteration and $(i+1)^{th}$ iteration, ω is the inertia coefficient and is given by equation (3) and C_1 and C_2 are the particles' personal acceleration coefficient and social acceleration coefficient.

$$\omega = \omega_{max} - \frac{\left(\omega_{max} - \omega_{min}\right) * Iter}{Max\,Iter} \tag{3}$$

3.2 Genetic Algorithm

Genetic algorithm (GA) is a metaheuristic process inspired by the process of natural selection and natural genetics introduced by John Holland. GA generates solutions for complex problems with the help of nature inspired operators such as mutation, crossover and selection. The search process starts with a randomly generated solution set called the population and each solution is called a chromosome. The individual solution is characterized by a set of parameters called gene. From the evaluated fitness function of the initial population, fittest individuals are to be selected for the next loop using crossover and mutation. Crossover refers to the process of producing new solutions called offspring by changing parts of the genes of parents (chromosome). Mutation in GA is the investigation of the search space, which is essential for the convergence of the optimization problem. Mutation operator involves the likelihood that any random bit in a genetic offspring will be overturned from its original state resulting in a new generation. As the population size is fixed, individuals with least fitness are removed providing path for the new offsprings to enter the population. The termination of the algorithm takes place once the convergence criterion is met.

3.3 Ant Colony Optimization

Ant colony optimization is a metaheuristic optimization method to solve difficult optimization problems. ACO imitates the foraging behaviour of ants. Ants communicate with the help of pheromone trails and it enables the ants to find the shortest path between their nests and the food sources. Marco Dorigo developed the algorithm in 1990s based on the characteristics of the real ant colony. ACO optimizes the solution in finding the shortest path by moving the ants around the search space based on the updated pheromone levels. ACO produces global ants and evaluates their fitness and updates the ant pheromone.

The transition probability of region k is calculated using the equation (4),

$$P_k\left(t\right) = \frac{t_k\left(t\right)}{\sum_{j=1}^{n} t_j\left(t\right)} \tag{4}$$

where $t_k\left(t\right)$ is the total pheromone at region k and n is the number of global ants.

Pheromone is updated by the equation (5),

$$t_i\left(t+1\right) = \left(1-r\right) t_i\left(t\right) \tag{5}$$

where r is the pheromones evaporate rate. The algorithm terminates when the sufficient iterations are performed or the optimized solution is achieved which specifies that all the ants move on to optimal path having the most concentrated pheromone.

3.4 Bat Algorithm

Bat algorithm (BA) is influenced by the behavior of micro bats, with varying pulse rates of emission and loudness. BA was proposed by Yang in 2010 to imitate the echolocation behaviour of bats. Echolocation is a kind of sonar based mechanism by which bats create loud and short pulses of sound. Bats are able to identify the difference between the obstacle and the prey by figuring out the distance of an object based on the echo that returns back to their ears. This echolocation helps bats to identify the prey and hunt them even in the whole darkness.

3.5 Cuckoo Search Algorithm

The Cuckoo Search algorithm (CSA) is a newly developed meta-heuristic optimization algorithm developed by Xin-She Yang and Suash Deb in 2009. Cuckoos are notorious birds because of their belligerent reproduction strategy. This nature inspired algorithm is based on this parasitic reproduction strategy wherein they lay their eggs in the nests of host birds, with Levy flights and random walks. Cuckoos pick a host nest where eggs are laid recently to lay its egg. After hatching, the cuckoo chick pushes the host eggs out of the nest in order to increase its food share. If the host bird finds out the cuckoo's eggs, it leaves their nests and build new ones or it can throw away the eggs that are not their own. To avoid this, cuckoos tries to produce eggs in different colors and patterns which in turn minimizes the risk of abandoning of eggs and thereby increases the re-productivity.

The new solution for t^{th} iteration is given by equation (6),

$$x_i^{t+1} = x_i^t + \alpha \oplus Levy(\lambda) \tag{6}$$

where α is the step size, i=1,2,…n, n is the population i.e., number of host nests, λ is the Levy exponent and $\oplus$ is the entry wise multiplication operator.

New nest near the old one will be build based on equation (7),

$$x_i^t = x_i^t + \in \left(x_i^t - x_j^t\right) \tag{7}$$

The best nest is identified by the cuckoo to lay the eggs and move on to the next generation.

3.6 Artificial Bee Colony Algorithm

Artificial Bee Colony simulates the behaviour of honey bees in search of food and was proposed by Karaboga in 2005. Bee colony/swarm basically consists of three groups of bees namely, employed bees, onlookers and scouts. Employed bee searches a food source and determines the nectar amount and dance in the hive. The onlooker bee observes the dance and then picks the source based on the dance and estimates the nectar quantity. This is achieved using a Roulette wheel selection process. The scout bees find new food sources instead of the abandoned sources.

Each employed bee X_i generates a candidate solution V_i in the neighborhood of the present position based on equation (8).

$$v_{i,j} = x_{i,j} + \phi_{i,j}\left(x_{i,j} - x_{k,j}\right) \tag{8}$$

where X_k is a randomly selected candidate solution $\left(i \neq k\right)$, j is a random dimension index selected from the set, $\phi_{i,j}$ is the random number within $\left[-1,1\right]$.

The probabilistic selection of the source by the onlookers is given by (9),

$$p_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j} \tag{9}$$

where fit_i is the fitness of the i^{th} solution in the swarm.

If a food source is abandoned, then the scout bee discovers a new food source to be replaced in place of abandoned one by equation (10).

$$x_{i,j} = lb_j + rand\left(0,1\right)\left(ub_j - lb_j\right) \tag{10}$$

where $rand\left(0,1\right)$ generates a random number within $\left[0,1\right]$ and lb and ub are the lower and the upper boundaries of the j^{th} dimension.

3.7 Wind-Driven Optimization

Wind-driven optimization (WDO) is a nature inspired optimization algorithm which is inspired based on the atmospheric motion of air parcels. This optimization algorithm uses four different forces that control the air parcels that move in the atmosphere in N-dimensional search space. The pressure gradient force pushes the air parcels in the forward direction, frictional force opposes the motion of air parcels in the forward direction, gravitational force acts in the vertical direction which attracts towards the origin and Coriolis force deflects the air parcels in the atmosphere. The expressions for the forces are given using equations (11) to (14) as:

$$F_{pg} = -\nabla \rho \delta v \tag{11}$$

$$F_f = -\rho \alpha \mu \tag{12}$$

$$F_G = \rho \delta v g \tag{13}$$

$$F_C = -2 © \mu \tag{14}$$

where ∇ is the pressure gradient, ρ is the air density, δv is the finite volume of the air, α is the frictional co-efficient, μ is the velocity vector of the wind, g is the acceleration due to gravity and © is the rotation of the earth.

The position and the velocity of the air parcels are updated in every iteration using equations (15) & (16).

$$v_{new} = ((1-\alpha) v_{old} - g_{old} + \left(\left|\frac{P_{max}}{P_{old}}\right| RT\left(x_{max} - x_{old}\right)\right) - \frac{cv_{old}}{P_{old}} \tag{15}$$

and

$$x_{new} = x_{old} + v_{new} " t \tag{16}$$

3.8 Bacterial Foraging Optimization Algorithm (BFOA)

Bacterial foraging optimization algorithm (BFO) is a swarm intelligence optimization algorithm that mimics the foraging behavior of E.coli bacteria. The BFO algorithm was first developed by 'Passino' and 'Kevin' in 2002. There exist four basic operations in BFOA namely Chemotaxis, Swarming, Reproduction and Elimination –dispersal. Chemotaxis phase mimics the movement of bacteria. Here, a bacterium can swim or tumble using its flagella towards the energy rich areas or away from the energy poor areas. In swarming phase, bacterium signals the other bacteria either with the attractant or repellent signal to move towards the nutrient rich environment or to move away from the nutrient poor environment. This is how cell-cell signaling happens in bacteria. In reproduction phase, the well-being status of bacterium is estimated by its accumulated fitness value. The unhealthy bacterium, which is the bacterium with higher accumulated fitness which gets less nutrition have no chance for reproduction and hence gets eliminated. Half of the bacteria which are in the less accumulated fitness value are selected to produce another half of the bacteria to keep the population size. In elimination-dispersion phase, some bacteria which experiences harsh environments will escape from the environment at a certain probability.

If θ is the position of a bacterium, then $\theta^i\left(j,k,l\right)$ represents the i^{th} bacterium at j^{th} chemotaxis, k^{th} reproduction, l^{th} elimination-dispersal. The equation denoting the tumbling or swimming motion of a bacterium is given by (17),

$$\theta^i\left(j+1,k,l\right) = \theta^i\left(j,k,l\right) + C\left(i\right)\frac{\Delta\left(i\right)}{\sqrt{\Delta\left(i\right)^T \Delta\left(i\right)}} \tag{17}$$

where $C\left(i\right)$ represents Chemotaxis step size and $\Delta\left(i\right)$ represents a random direction vector in the range [-1,1]. The fitness value of i^{th} bacterium at j^{th} chemotaxis, k^{th} reproduction, l^{th} elimination-dispersal can be computed using the equation (18).

$$J\left(i,j,k,l\right) = J\left(i,j,k,l\right) + J_{cc}^i\left(\theta^i\left(j,k,l\right), P\left(j,k,l\right)\right) \tag{18}$$

The position is updated using equation (17) and the fitness function is computed with respect to the new position using (18). The best fitness value is updated after comparing the computed value with the existing best fitness value. The algorithm terminates when sufficient runs are performed or the optimized solution is achieved.

3.9 Grey Wolf Optimization (GWO)

Grey wolf optimization algorithm is a meta-heuristics algorithm developed by Seyedali Mirjalili and team in 2014 based on the leadership behaviour and hunting mechanism found in grey wolves. The grey wolf hunts the large prey in packs and relies on cooperation among the individual wolves. The pack of wolves has been categorized into different forms based on their participation in the hunting mechanism. Wolves that lead the activities of the pack are called 'alpha' and the wolves in the next level which reinforce the instruction of alpha are called 'Beta'. The next level of wolves are called 'delta' which are of different categories like scouts, sentinels, elders, hunters, caretakers etc. The fourth category of the wolves are called 'omega' which are considered as scapegoat in the pack and are the least important individuals in the pack of wolves. The main phases of grey wolf hunting process are

(i) Tracking, chasing and approaching the prey, (ii) Pursuing, encircling and harassing the prey until it stops moving and (iii) Attack towards the prey.

3.10 Firefly Optimization Algorithm (FOA)

Firefly optimization algorithm is a meta-heuristic algorithm developed by Xin-She Yang in the year 2008 based on the flashing patterns and behaviour of fireflies. Firefly algorithm uses a set of idealized rules like, (i) Fireflies are attracted towards the other fireflies, (ii) The attractiveness depends on the brightness or the intensity of the light, i.e., firefly flashing with less brightness will be attracted towards the brighter firefly and (iii) The brightness of the firefly is determined by the landscape of the objective function. The position of the firefly gets updated in every iteration based on the equation (19).

$$x_i^{t+1} = x_i^t + \beta_o e^{-\gamma r_{ij}^2} \left(x_j^t - x_i^t\right) + \alpha \varepsilon_i^t \tag{19}$$

where β_o is the attractiveness of the distance $r = 0$, α is the randomization parameter and ε_i^t is a vector of random numbers drawn from a Gaussian distribution at time t. The intensity of light emitted by the firefly at a distance r is given by, $\left(r\right) = \frac{I_o}{r^2}$, where I_o, is the light intensity generated at the light source. If γ is the absorption co-efficient, then the light intensity, I at a distance r is given by, $I = I_o e^{-\gamma r^2}$. The attractiveness function is given by, $\beta\left(r\right) = \beta_o e^{-\gamma r^m}$, $m \geq 1$. Also, the distance between any two fireflies is given by equation (20),

$$r_{i,j} = \left|x_i - x_j\right| = \sqrt{\sum_{k=1}^{d}\left(x_{i,k} - x_{j,k}\right)^2} \tag{20}$$

4. ENERGY MANAGEMENT IN HOMES, BUILDINGS

Energy management is mostly achieved in homes or buildings through demand side management. DSM helps in scheduling the various appliances/devices/loads thereby bringing in flexibility to the load curve. Figure 3 shows the processes involved in Energy Management in homes, buildings and microgrid.

Home energy management system (HEMS) reduces the electricity bill and PAR by optimally scheduling the appliances and energy storage systems (ESS) in accordance with the dynamic pricing of electricity. GA, BPSO, WDO, BFO and hybrid GA-PSO (HGPO) algorithms are used to solve this constrained optimization problem (Ahmad et al.,2017). HGPO algorithm outperformed all other algorithms with respect to both objectives. As GA reduces PAR effectively and BPSO reduces the electricity bill, these two algorithms are chosen for hybridization. Minimization of waiting time is considered along with reduction in electricity bill in (Rahim et al., 2016) and the solutions are obtained using GA, BPSO and ACO. GA provides better solutions in less time compared to BPSO and ACO mainly due to two features, crossover and mutation.

Load management, reduction in electricity bill, PAR and waiting time are considered as a multiple objective function and the solutions are obtained using the Pareto front (Khan et al., 2019). An extended BSO algorithm, MBBSO and a hybrid algorithm combining MBBSO and MOCSO (MBHBCO) are used for the optimal day ahead scheduling of appliances. Hybridization of the algorithm is done using the loosely coupled strategy. GWO algorithm is used for device scheduling under eight different scenarios in (Molla et al., 2019) considering time of use pricing scheme. GOA and BFA are used for appliance scheduling in an office to achieve reduction in bill, PAR and user discomfort (Ullah et al., 2019). It is found that energy bill reduction leads to increase in user discomfort and hence a multi objective approach is helpful to deal with these conflicting objectives. An energy management controller based on various evolutionary algorithms like GA, WDO, BFO, BPSO and a hybrid algorithm is proposed for realizing objectives like reduction in PAR, emissions, electricity bill etc. in a smart building (Rehman et al., 2021). Firefly algorithm and Lion algorithm is combined to form a hybrid algorithm and it is used for optimal load scheduling for a campus building (Ullah et al., 2021). Electricity cost reduction is achieved without much increase in the waiting time of the customers.

Research on building energy management system mostly concentrated on reduction in energy consumption of HVAC systems (Mariano et al., 2021). Based on the type of building, other systems in the building can also account for higher power consumption and hence these systems have to be considered by the BEMS. Almost all works on BEMS considers the minimization of energy cost and maximization of user comfort using multi-objective algorithms (Aguilar et al., 2021). Hybridization of optimization algorithms results in better performance in terms of achieving the objectives such as minimum power consumption and maximum comfort (Wahid et al., 2020). Lion's algorithm is used for energy management of industrial loads considering renewable sources and energy storage units (Hussain et al., 2022). Social spider optimization algorithm is used for minimizing the cost, emissions and dump energy for realizing an optimal house energy management system (Suruli et al., 2020).

5. ENERGY MANAGEMENT IN MICRO GRID/DISTRIBUTION NETWORK

Microgrid is a network interconnecting loads, DGs and ESS, and it can be interconnected to the main grid through the point of common coupling (PCC). Micro grid can be operated either in grid connected mode or in islanded node. Various micro grids can be interconnected to the grid and operated optimally to improve the reliability and performance of the distribution network. EMS helps in managing the various entities in a microgrid thereby enabling its smooth and optimal operation. Energy scheduling helps MGs to deal with the inherent uncertainties in renewable DG output as well as load.

EMS helps to regularize the power fluctuations by meeting the load – generation balance in a microgrid. This is achieved by optimizing the parameters of the fuzzy logic controller of the EMS using PSO and DE algorithms (Arcos et al., 2021). GA is used to improve the performance of FA in optimizing energy usage and user comfort in a smart building (Wahid et al., 2019) and the results are compared with artificial bee colony algorithm. Ant lion Optimization algorithm is used for optimal energy management in a microgrid by minimizing a cost function (Roy et al., 2019). Lightning search algorithm (LSA) is used to optimize the performance of an energy management controller in a micro grid. The objectives of the controller are reduction of emissions and cost expenses related to energy generation and energy exchange (Roslan et al., 2021a). This algorithm mimics the process of lightning and the mechanism of step leader propagation using projectiles and exhibits better performance compared to PSO and BSA algorithm. Similar work is carried out by the authors of (Roslan et al., 2021b), wherein the optimal operation of DERs is also considered as one of the objectives of the energy management controller. Five MGs are considered to be connected to an IEEE 14 bus system and their operation is optimized by the EMS. Sparrow search algorithm is utilized for obtaining the optimal scheduling of linear and non-linear loads in a micro grid through incentive based demand response programs (Raghav et al., 2022).

Uncertainties related to renewable DG output, electricity price, and load demands are also considered. The algorithm is developed based on the behaviour exhibited by sparrows in searching food and escaping from predators. An enhanced adaptive bat algorithm is proposed (Yang et al., 2021) for optimal scheduling of DGs in a microgrid. The drawbacks of the original bat algorithm are rectified with the help of adaptive weights and sharing of information. The objective is to reduce the generation cost along with the power balance constraints under different scenarios including equipment malfunction and renewable DG output fluctuations. A new algorithm, PSA which simulates the behavior of Porcellio Scaber (PS), a species of woodlice is used for optimizing the performance of a three phase EMS between two micro grids which are not connected to the grid (Keshta et al., 2021).

EMS optimally schedules the sources and the loads in the two micro grids keeping the energy cost at its minimum. Cuckoo search algorithm is used for load scheduling minimizing the peak load, user inconvenience and energy cost (Shaban et al., 2021). It also helps in maximizing the output of the renewable generators considering time of use pricing. EMS helps in coordinating the power exchange among different micro grids as in (Elmetwaly et al., 2022), thus accounting for the uncertainties due to renewable power sources. The objectives considered by the system are reduction in maintenance and emission costs and they are minimized using marine predator algorithm (MPA). This algorithm emulates the foraging behaviour of predators in the marine ecosystem. Ant lion optimizer is used to arrive at the optimum mix of generation and load using demand response program to minimize the cost and emissions (Alazemi et al., 2019).

6. KEY TAKEAWAYS

Non-linear optimization problems can be solved either using deterministic methods or by means of metaheuristic algorithms. Deterministic methods are not capable of giving a suitable solution for high dimensional nonlinear optimization problems. Metaheuristic algorithms find the solutions using two techniques namely exploration and exploitation. Exploration helps in locating diversified solutions in the search space whereas exploitation concentrates the search process in the area of best solutions. The process of successfully arriving at the solution depends upon the balancing between exploration and exploitation. The application of new emerging algorithms to EMS applications is a prosperous area of research. The new algorithms can reduce the computational cost and handle the complex multi-objective problems with ease.

Possibilities of hybridization with other traditional algorithms can lead to many advantages and help in achieving the objectives more efficiently. The most commonly used population-based algorithms are particle swarm optimization (PSO), differential evolution, gravitational search algorithm (GSA), backtracking search algorithm (BSA), harmony search algorithm etc. They are most commonly used for solving load scheduling or appliance scheduling in for optimal operation. Most of these algorithms have a large set of parameters and the optimal solution largely depends upon the correct choice of these parameter settings. Some algorithms have a tendency for the final solution to fall into local optimum. The performance of many new emerging algorithms is still in the initial phase and hence there won't be much prior knowledge about its convergence, robustness, and the capability to find an optimal solution. As the number of decision variables increases, the computational efficiency also reduces. Table 1 gives an overview about the various applications of optimization algorithms for realizing energy management systems.

Certain metaheuristic techniques like PSO, DE are preferred for their coherence, robustness, precision, fast convergence, and global search exploration to find optimal solution of proposed objective function formulation. DE algorithm has fewer parameters whereas PSO algorithm converges rapidly without the need for complex calculations. The CS algorithm is a more recent substitute to PSO that simulates the egg laying behavior of some cuckoo species. The GWO algorithm has predominant investigation and exploitation qualities than other swarm intelligence techniques. Firefly algorithm (FA) is an easily realizable and robust technique. But there is a lack of balance between the exploration and exploitation which can deteriorate the solution quality.

The ALO algorithm also has merits in solving constrained problems with separate search spaces as in the optimization of energy management systems. GA is most suitable for complex non-linear models, but it does not assure optimality even after arriving at the global optimum. ACO is a meta-heuristic optimization approach that is used to solve discrete combinatorial optimization problems. The CSA is suitable for use in optimization problems, like energy optimization. The performance of any algorithm improves if it concentrates more on global search instead of local search. The number of parameters should be less and it should have faster convergence rate. Overall the implementation of the algorithm should also be easier. The improvements in various parameters using different algorithms in Energy management system are shown in Fig. 4 (Amjad et al., 2020; Rahim et al., 2016; Imran et al., 2020; Awais et al., 2018)

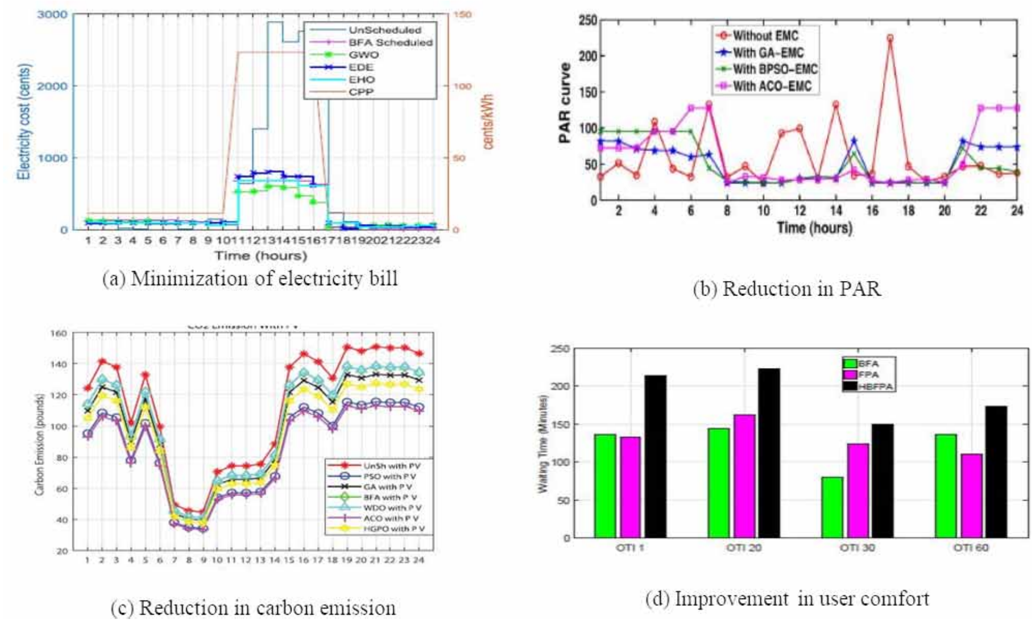
Table 1.
Overview of various optimization algorithms used for EMS

Ref. No.	Algorithms	Objectives	Application	Assumptions/ Limitations
Ahmad et al., 2017	GA,BPSO,WDO,BFO, Hybrid GA/PSO	Minimization of Electricity bill	Home Energy Management system	Uninterrupted utility power supply
Rahim et al., 2016	GA,BPSO,ACO	Minimization of waiting time and reduction in Electricity bill	Smart Energy management controller for single and multiple homes	Power capacity limitations for various appliances
Molla et al., 2019	GWO	Minimization of Energy cost, PAR, peak load demand	Home Energy Management system	Appliances are working at its maximum power rating
Ullah et al., 2019	GOA,BFA	Minimization of Electricity bill, PAR, and frequency of interruptions	Office Energy Management	Limit on total energy consumption by various appliances
Rehman et al., 2021	GA,WDO,BPSO,BFO and hybrid algorithm	Reduced Electricity bill, PAR, Carbon emission and improved user comfort	Energy Management in Smart Building	Availability of RES for 90% of the scheduled time
Hussain et al., 2022	LOA	Minimization of total energy cost, PAR, Hourly load and Waiting time	Energy Management in Industrial Areas	Not specified
Arcos et al., 2021	PSO,DE	Smoothen the power profile exchange with the grid	EMS of residential microgrid	Not specified
Roy et al., 2019	ALO	Minimization of Electricity production cost	Energy management of microgrid	Power and ramp limits
Roslan et al., 2021a	Lightning Search Algorithm	Minimization of the operating cost of DER and Optimal use of Energy Storage	Optimized controller for microgrid	Energy limits for the storage system
Roslan et al., 2021b	Lightning Search Algorithm	Minimization of total operating cost of DER and reduce emission	Optimized controller for microgrid energy Management	Power limits for DER and Energy storage
Raghav et al., 2022	Sparrow Search Algorithm	Minimization of DG units Procurement Cost and utility energy exchange cost	Energy Management in Microgrid	Power generation limits for DG and Power balance, power flow and voltage constraints
Yang et al., 2021	Enhanced Adaptive BAT algorithm	Minimize the generation cost of DG	Microgrid Energy Scheduling	Power limits for DG and Energy Balance Constraints
Keshta et al., 2021	Porcellio Scaber Algorithm	Minimize the total daily generation cost	Energy Management system for Interconnected microgrids	Power generation limits, power exchange limits and voltage limits
Shaban et al., 2021	Cuckoo Optimization Algorithm	Minimize peak load, Energy cost and User inconvenience	Load scheduling for Smart grid systems	Presence of Energy storage is not considered and scheduling interval limits
Elmetwaly et al., 2022	Marine Predator Algorithm	Minimization of maintenance and emission cost for fossil fuel generators	Energy Management system for Interconnected microgrids	Generation capacity and Power balance constraints, charging/discharging limits for BESS

7. CONCLUSION

This paper gives a brief overview about the different nature inspired algorithms used for realizing optimal energy management systems at homes, offices, buildings and at the micro grid level. The various objectives considered by the authors for problem formulation are also discussed. Many new algorithms are emerging and these algorithms and their performance in solving the optimization problem are analysed in detail.

Figure 4.
Improvement in various parameters using different optimization algorithms



(a) Minimization of electricity bill

(b) Reduction in PAR

(c) Reduction in carbon emission

(d) Improvement in user comfort

Most of the studies concentrated on developing energy management systems for residential homes, mostly by scheduling the appliances using demand response programs. At the grid level, the objectives considered are smoothing the peak load fluctuations or optimizing the energy exchange between the various sources in the microgrid. Future research in this area can focus more on considering real time data for realizing EMS and also loads such as electric vehicles during DSM. With respect to the various algorithms used, if the number of parameters of the optimization algorithm to be tuned is less, then the complexity of computation reduces and the global optimum solution can be reached easily. All the algorithms are sensitive to the values of its parameters and hence these have to chosen carefully depending upon the objectives and constraints. We cannot conclude that one algorithm is superior compared to another one for arriving at the global optimum solution. The critical point to be taken care of during optimization is to maintain the balance between the exploration and exploitation techniques, so as to avoid any local minima/maxima in the search space.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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