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SMART GRID RENEWABLE ENERGY DISTRIBUTION FOR COMMERCIAL BUILDINGS USING GENETIC FUZZY SWARM ENHANCED RECURRENT EXTREME NEURAL LEARNING

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ABSTRACT

With growing need of energy on commercial building, renewable energy storage in smart grid becomes more essential. However, the stability and reliability of smart grid on renewable energy distribution on multi-variant power system requirement in commercial buildings becomes the major problem. To improve reliability and stability of smart grid renewable energy distribution, Genetic Fuzzy Swarm Recurrent Extreme Neural Learning based Optimal Load Shifting (GFSRENL-OLS) Model is introduced. The energy consumption and electricity cost of GFSRENL-OLS Model is reduced by 30% and 61% when compared to existing methods.
Keywords: commercial building, renewable energy storage, smart grid, multi-variant power system, energy consumption

INTRODUCTION

Solar energy is readily available form of renewable energy among all available options. Due to unpredictable nature, energy retailers and consumers are left with slew of questions. According to the study conducted in Solar Energy, the earth receives 174,000 terawatts of solar radiation with 30% of radiation reflected back into the atmosphere. The clouds, oceans, and land masses absorb the majority of the remaining emissions. A new load shifting-based optimal demand-side management (DSM) model was designed in [1] for scheduling residential user appliances. Virulence Optimization Algorithm (VOA) and Earth Worm Optimization Algorithm (EWOA) shifted their time slots of shiftable appliances. However, energy loss was not minimized. A consensus algorithm-based coalition game theory was introduced in [2] to perform optimal demand management scheme for multi-agent smart microgrids (SMGs). The consensus algorithm carried out data transfer among neighbors in SMGs. However, the PAR was not minimized by designed game theory. An algorithm-based optimal DSM was introduced in [3] to improve smart grid efficiency with minimal electricity consumption cost. But, the computation cost was not reduced. An innovative multi agent-based heuristic optimization system was designed in [4] to address renewable energy system. But, the energy loss was not reduced by designed system. The

Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4779-4795

smart grid was discussed in [5] with renewable energy. The renewable energy and distributed power was discussed in smart grid system. However, the reliability level was not improved. The renewable energy resource distribution was carried out in [6] on quantitative empirical basis. Lorenz curves and Gini coefficients were determined for fossil fuels and renewable energy types. However, the computational complexity was not minimized by designed distribution. A new metaheuristic optimization method was introduced in [7] for addressing the renewable energy sources (RES) allocation in distribution system. The designed algorithm was employed to allocate the wind turbines and solar photovoltaic arrays with power loss minimization. Though the power loss was minimized, energy consumption was not reduced by designed metaheuristic optimization method. A distributional picture of world renewable energy was discussed in [8] with club convergence algorithm depending on renewable energy generation. But, the energy loss was not reduced by designed convergence algorithm. A combined data-driven and model-driven method was introduced in [9] of distribution network reliability of renewable energy distribution network. The designed method improved reliability with fault consequence analysis. computational complexity was not minimized. A multi-objective distributional robust optimization (DRO) model was introduced in [10] for H-RE-CCHP development. But, power loss was not In order to address these issues, Genetic Fuzzy Swarm Recurrent Extreme Neural Learning based Optimal Load Shifting (GFSRENL-OLS) Model is introduced.

GFSRENL-OLS Model is introduced to enhance reliability level and stability level of smart grid renewable energy distribution.

GFSRENL-OLS Model computes hour and appliance operation time for demand conditions of commercial power system requirements

Genetic Fuzzy Swarm Optimization (GFSO) identifies the optimal time slot for performing the reliable and stable state of smart grids to minimize energy loss.

RELATED WORKS

A new backup protection method was introduced in [11] to guarantee stable operation for low voltage distribution network. However, energy cost was not minimized by backup protection method. A multi-objective distributional robust optimization model was designed in [12] for identifying the optimal location of wind turbine and solar photovoltaic (PV). But, energy loss was not minimized. A unified out-of-distribution (OOD) detection framework was designed in [13] for intelligent PHM to improve reliability. Distribution locational pricing mechanism was introduced in [14] for distribution lines linked by soft open points (SOPs) with reasonable pricing policy. However, the computational complexity was not reduced. A new multi-state modeling and reliability analysis method was designed in [15] for new distribution network with energy storage charge–discharge plan. But, electricity bill was not minimized A routing algorithm was designed in [16] for energy router. But, PAR was not minimized A comprehensive review was carried out in [17] on current technologies to perform distribution system operators. The volt-var technology was employed distribution network. Gorilla Troop Optimizer (GTO) algorithm was introduced in

Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4779-4795

[18] to address optimization problem. Single-objective particle swarm optimization (SOPSO) and multi-objective particle swarm optimization

Nomenclature			
H	number of appliances	G	Solar radiation.
T	Threshold	G_{ref}	Reference solar radiation
h	time slot	$c \in R^{n_z}$	Controlled output
op	Observation period	T_{amb}	Ambient temperature.
TD_{ni}	LOT of Aappliance	$NOCT$	Nominal operation temperature.
K	Power coefficient at different temperatures.	T_{ref}	Reference temperature under the standard conditions.
θ_2	Maximum edges of starting and ending times of the appliances	θ_1	Minimum edges of starting and ending times of the appliances
$E_{ni,h}$	Energy consumed by appliance during time slot	θ_{ni}, h	Collection of shiftable appliances operating in time slot
E_T	Energy Demand	$b \in R^{n_y}$	Measured output.
E_{RES}	Energy generated daily	$d \in R^{n_w}$	variations in space
$I(t)$	Input layer	$v \in R^{n_w}$	control input
ED_k	Energy demands of residential loads	$a \in R^n$	State vector
t	time instant	SS	Stochastic selection
$P_{s,N}$	Power output of Nth solar photovoltaic	FF	Fitness function.
$P_{PV}{}^{nom}$	Nominal power of PV under test conditions.	$Hd(t)$	Output of hidden layer
N	Solar PV number.	$O(t)$	output layer
w_{oh_2}	Weight between hidden layer 2 and output layer.	$w_{h_1h_2}$	Variable weight between hidden layer 1 and hidden layer 2.

(MOPSO) were introduced in [19] to enhance the microgrid performance in renewable energy resources (RERs) with randomized natural behavior. But, reliability was not improved. A consensus algorithm-based coalition game theory was introduced in [20] for optimal demand management scheme in multi-agent smart microgrids (SMGs). The consensus algorithm carried out information and data transfer among neighbors in multi-agents SMGs. But, energy loss was not minimized. A bi-level model was introduced in [21] for smart distribution network under renewable energy resources. The reformulation method with Karush–Kuhn–Tucker (KKT) condition addressed energy consumption problems. The energy scheduling issues were addressed in [22] for residential smart electrical distribution grid (RSEDG) in demand side management (DSM). RSEDG minimized operation cost and emission pollutions in generation side. A Stackelberg game-based collaborative optimization approach was introduced in [23] for distribution network. A comprehensive model was introduced in [24] for resilient exploitation of intelligent distribution network with physical-cyber-attacks. The resilient network operation was carried in normal mode without physical-cyber-attacks.A comprehensive approach was introduced in [25] for handling the renewable energy sources in smart grid environments. The partitioning strategy was introduced in [26]. The local real-time control was carried out for reactive power.A sufficient state estimation algorithm was introduced in [27] for monitoring distribution systems in renewable energy sources. The big data analytics implementation was carried out in [28] for smart grids and renewable energy power utility. A five-step approach was employed for smart grid stability prediction. Home Energy Management System (HEMS) was designed in [29] using renewable energy. HEMS integrated into Smart Grid (SG) scheme for monitoring and scheduling

Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4779-4795

appliance operational activities to minimize energy consumption. A distributed method was designed in [30]. Each retailer consumed energy in their area through Mixed Integer Linear Programming (MILP). A Recurrent Neural Network (RNN) based LSTM framework was introduced in [31] for Science Block (SCB) each minute to develop DSM program. Digital twin simulation was introduced in [32] to improve energy management. The designed scheme performed system behavior prediction in diverse scenarios. A comprehensive review was carried out in [33] on sustainable airport energy ecosystems with renewable-grid-storage-flexibility from airport energy ecosystem constitutions. Recurrent Trend Predictive Neural Network based Forecast Embedded Scheduling (rTPNN-FES) was designed in [34] for residential demand control. rTPNN-FES forecasted renewable energy generation and scheduled household appliances. URJA with access control scheme was designed in [35]

METHODOLOGY

A smart grid combines the communication networks with electrical grid to perform efficient deployment. A mixed integer linear programming model was designed in [36] with integrated operations planning and energy management for renewable energy generation. The objective is to examine the user perceptions of smart grid reliability and assess their success factors in effort. In order to address issues, Genetic Fuzzy Swarm Recurrent Extreme Neural Learning based Optimal Load Shifting (GFSRENL-OLS) Model is introduced. Fig. 1 explains the architectural diagram of-OLS Model.

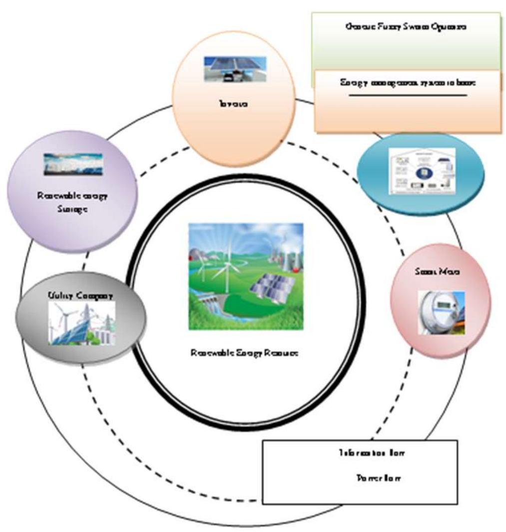


Fig. 1 Architecture Diagram of GFSRENL-OLS Model

A smart meter is positioned between home area network and utility. electricity consumers are categorized to traditional consumers, intelligent consumers, and intelligent prosumers. A standard BMS (StBMS) was introduced in [38] for individual prosumer self-consumption (SC). StBMS guaranteed REC energy independence from national grid and resulting in more incentives for all stakeholders. A stochastic real-time process was employed in [37].

Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4779-4795

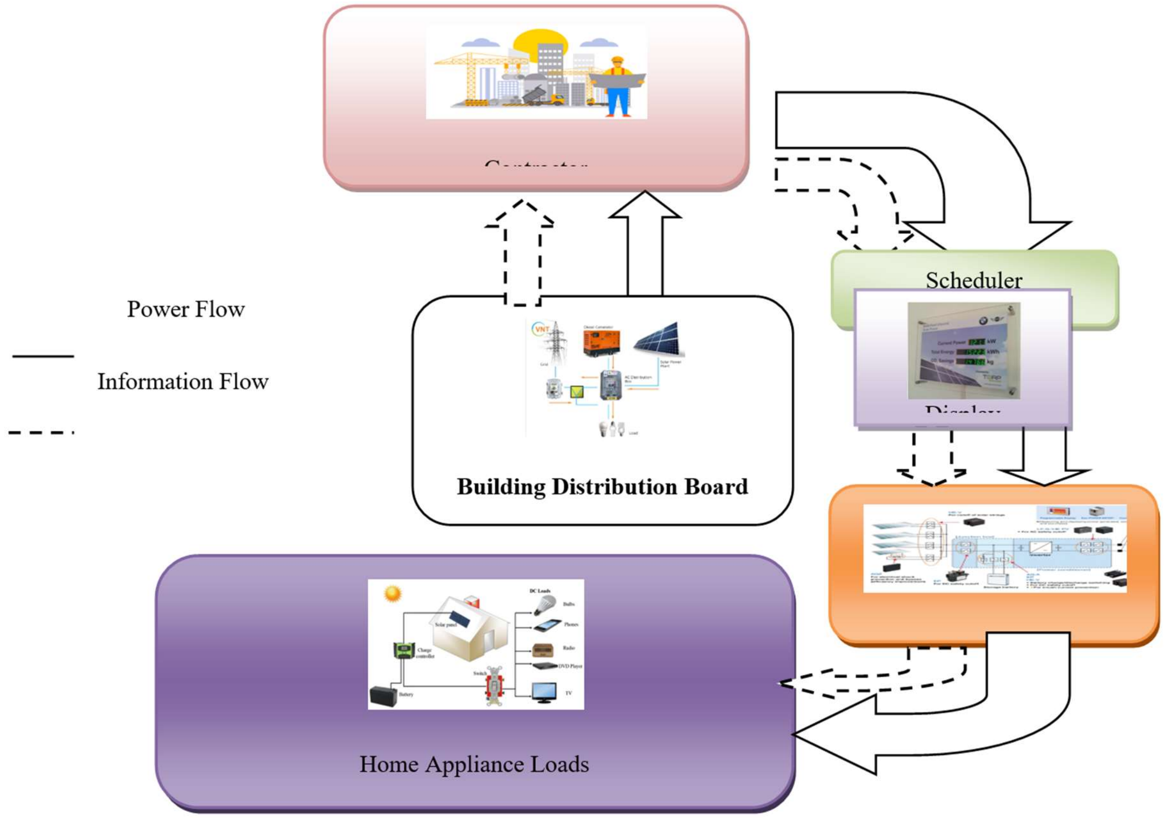


Fig. 2 Energy Management Systems

Fig. 2 explains the energy management system. In GFSRENL-OLS Model, energy management system is used to monitor, control and conserve the energy in building. All load types are met through integrating the renewable and energy storage into the utility grid. The power grid and RER are considered as the single node. In order to meet the peak demand, the optimization process is carried out to the home loads. ESDs are used during on-peak hours. It is used to meet the energy demand of residential loads through grid energy, renewable energy or energy storage systems based on electricity price in particular hours. A time series based energy forecasting system was introduced in [39] with solar home database. The on-site RERs and storage system is served as the first source of energy for supplying energy to the loads. The load-side management system minimized the amount of energy obtained from utility. An on-site renewable and storage energy with building energy management model minimized the grid peaks during high energy demand. system has smart meters, data centers and communication network to integrate data into application platforms.

3.1 Energy Management

A load-side EMS depending on Time of Use (ToU) dynamic pricing is carried out for residential building. With help of smart meter, Smart Scheduler (SS) attains the grid differential price pattern and varies the user hourly load level consistent with pricing signal. SS optimized the electrical appliance utilization through shifting the maximum allowable load from peak to off-peak times. SS computes the cost of hourly energy utilization and transferred the load from utility grid. When

Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4779-4795

SS is not incorporated into EM system, energy is assigned to appliances on a first come and first serve basis. When SS is accessible, power allocation to group of appliances is implemented. It is to increase the economic benefit and to minimize the peak costs. The designed model minimized the grid power dependence and increased the peak demand power consumption. The designed pricing strategy increased use of RERs. EMS comprised several components, namely building or home grid, display device and electrical appliances. The home is equipped with intelligent appliance decision-making and scheduling device. EMS is combined into EM architecture and works in conjunction with the appliances. The power demand of single home served as consumer and generator of power surges. The smart meter presents the energy price signals. The SS determines the ON/OFF control signals for household appliances in the efficient manner. Consider the house comprising 'n' number of appliances 'H=a_1,a_2,a_3,a_4……..a_n'. Assume that 'op' symbolizes the observation period with two loads, namely Interruptible Loads (IL) and Base Loads (BL). A washing machine, an electric water heater, a cloth dryer, and an electric vehicle are known as interruptible loads. Base Loads comprised the refrigerator and illumination source. After activation, interruptible appliances varied at any time. A scheduling problem arises when maximum edges of starting and ending times of the appliances goes beyond zero (i.e., A > 0). Optimized control behavior over shiftable loads attains the end user objective. 'θ_ni,h' represent the collection of shiftable appliances operating in time slot 'h'. The base loads are taken as the unscheduled. The assumption is done as end user indicated that they are unwilling to reschedule the loads. Every appliance has fixed count of available time slots for operation. Ever appliance complete their task within 24 h. Because of their condition, SS functioned on load shifting principle. Every appliance tolerate the amount of delay '〖TD〗_ni' denoted as,

$$\theta_1 \leq TD_{ni} \leq \theta_2 \quad (1)$$

From (1), '〖TD〗_ni' symbolizes the LOT of the appliance. 'θ_1' and 'θ_2' are minimum and maximum edges of starting and ending time of the appliances respectively. Table 1 describes the power consumption of home appliances

Table 1 Power Consumption of Home Appliances

Load type	Appliances	Operating time	Rated power (kW)
IL	Clothes washer	1–4 PM & 1–3 AM	1.5
	Clothes dryer	1–4 AM, 9–12 AM & 7–10 PM	3
	Electrical vehicle	8–11 PM, 5–8 AM & 9–11 AM	3.5
	Electric water heating apparatus	5–11 PM, 1–2 AM, 4–6 AM & 7–8 AM	4.5
BL	Refrigerator	All time	1
	Lights	All time	1.5

The following equation defines the upper and lower bounds of 'TD_{ni}'

$$0 \leq \theta_1 < \theta_2 \quad \theta_1 \leq \theta_2 < 24 \quad (2)$$

'$E_{ni,h}$' represent the energy consumed by appliance 'ni' during time slot 'h', the home overall demand energy 'E_T' is given as,

$$E_T = \sum_{i=1}^{C} \sum_{h=1}^{24} E_{ni,h} \quad (3)$$

In addition, the household generates 80% of their total demand through renewable energy sources. The user gets associated with their utility. $E_{RES,h} \forall$ h $\in \{1,2,3, \ldots ,24\}$. The daily generation is given as,

$$E_{RES} = \sum_{h=1}^{24} E_{RES,h} \quad (4)$$

From (4), 'E_{RES}' symbolizes the total amount of energy generated daily.

3.2 Load Shifting Model

The new load shifting-based optimal demand side management is performed to serve building block for optimization. All load types are combined through renewable and storage energy into utility grid. An equivalent power grid is considered as a single node. For addressing the peak demand, optimization program applies power to home loads. Energy storage devices are used during the on-peak hours to meet energy demand of residential loads based on electricity price The on-site RERs and storage system serve as 'first choice' source of energy for supplying energy to loads. The load-side management system reduces the amount of energy obtained from the utility. An on-site renewable and storage energy combined with building energy management model to minimize the grid peaks during high energy demand. Depending on Time of Use (ToU) pricing, load shifting process is carried out to schedule the power use of appliances in building. The load scheduling is carried out to keep track of electricity appliances.

4. Genetic Fuzzy Swarm Recurrent Extreme Neural Learning based Optimal Load Shifting

Extreme learning machines are the feed forward neural networks for classification with single layer or multiple layers of hidden nodes. The parameters of hidden nodes are tuned. The hidden nodes are randomly assigned and not updated. The output weights of hidden nodes are learned in single step to learn the linear model.

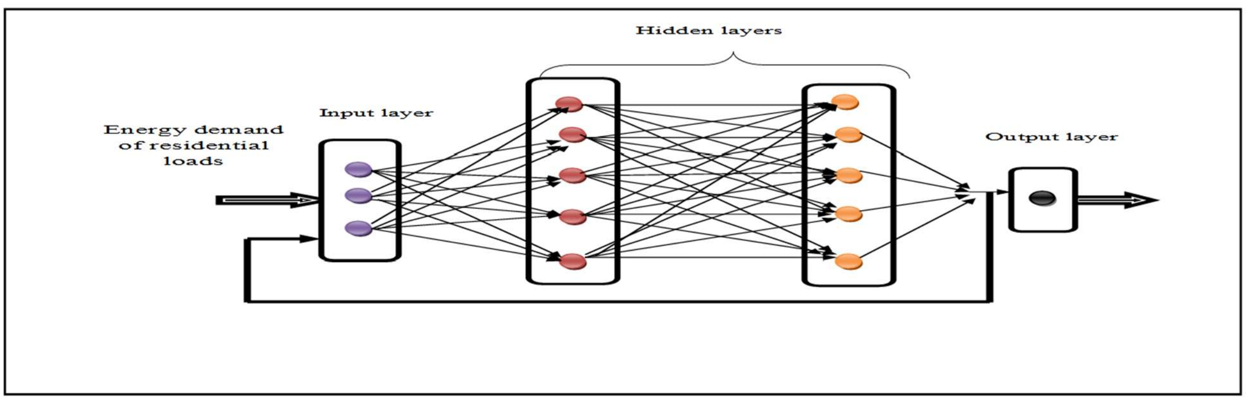


Fig. 3 Structure of Recurrent Extreme Neural Learning

$$In(t) = \sum_{k=1}^{m} ED_k * w_{ini} + B \quad (5)$$

From (5), $In(t)$ denotes the input layer for collecting the energy demands, 'ED_k' represents the energy demands of residual loads. 'w_{ini}' denotes the optimized weight of input layer. 'B' symbolizes the bias to regulate the output with weighted sum of inputs to the neuron. Then in GFSRENL-OLS Model, the energy demands are sent to the hidden layer 1. In that layer, the multiple residential load conditions are computed with stochastic recurrent neural network patterns on renewable energy storage and distribution. The important parameters influence PV output production like temperature and sunlight. It is possible to express the power output of Nth solar photovoltaic ($P_{s,N}$) panel. It is formulated as,

$$P_{s,N} = P_{PV}{}^{nom} \frac{G}{G_{ref}} \left[1 + K(T_{amb} + \left(\frac{N-20}{800} G\right) - T_{ref}\right] \quad (6)$$

From (6) '$P_{PV}{}^{nom}$' represent the nominal power of PV under test conditions. 'N' symbolizes the solar PV number. 'G' symbolizes the solar radiation. It is formulated as,

$$G_{ref} = 1\, kW/m^2 \quad (7)$$

From (7), 'G_{ref}' represent the reference solar radiation. 'K' symbolizes the power coefficient at different temperatures. 'T_{amb}' symbolizes the ambient temperature. '$NOCT$' symbolizes the nominal operation temperature. 'T_{ref}= 25◦C' denotes the reference temperature under the standard conditions. The renewable energy is generated from the adopted solar PV sources. Solar energy is used for storage purposes or to power residential appliances between hours of h7 and h19. The solar energy is not available from h1 to h7 and h20 to h24. Consequently, an optimization algorithm is designed to manage the residential loads during peak hours. Grid of high peaks at off-peak time has achieved through stored energy utilization. During peak hours, users rely on RES stored energy than the utility grid to minimize electricity costs and high peaks. In addition, optimization resulted in grid stability. ESD saved the additional energy and supplied during underload circumstances. After that, the computed multiple residential load conditions are sent to the hidden layer 2. In that layer, Genetic Fuzzy Swarm Optimization (GFSO) is used in GFSRENL-OLS Model to perform extreme learning on reliable and stable state of the smart grids to reduce the energy loss, to identify the optimal grid stability, and reliable power distribution in worst case scenario of multi-variant power system demands. Let us consider that house with the number of appliances '$a_1, a_2, a_3, \ldots . a_n$,'. '$H$' symbolizes the observation period with Interruptible Loads (IL) and Base Loads (BL). A washing machine, electric water heater, cloth dryer and electric vehicle are included in IL. BL comprises the refrigerator and illumination source. The scheduling problem exists when number of controllable appliances exceeds zero. An optimized control behavior over shiftable loads is used to attain the end user objective.

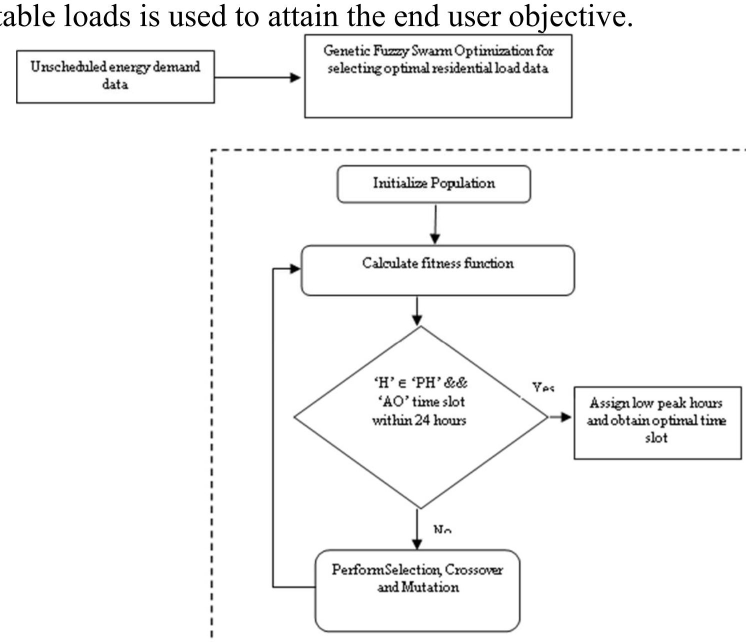


Fig. 4 Architecture Diagram of Genetic Fuzzy Swarm Optimization

Fig. 4 explains the architecture diagram of Genetic Fuzzy Swarm Optimization, Genetic Fuzzy Swarm Optimization is used to handle the unscheduled residential loads during peak hours. The optimal time slot is selected after determining the fitness function (i.e., appliance operation time (AO) and hour (H)). When the fitness function satisfies the threshold criteria, the low peak hours are selected and attained optimal slot. When the criteria are not satisfied, selection, crossover and mutation process is performed to choose the global optimal solution using Genetic Fuzzy Swarm Optimization through satisfying all criteria. The fitness function is computed with fuzzy controller. The fuzzy rules (i.e., 'Hour' ∈ 'Peak Hour' && 'Appliance Operation time slot within 24 hours) are used to determine the stability analysis and controller design. Fig. 5 describes the membership function in fuzzy concept.

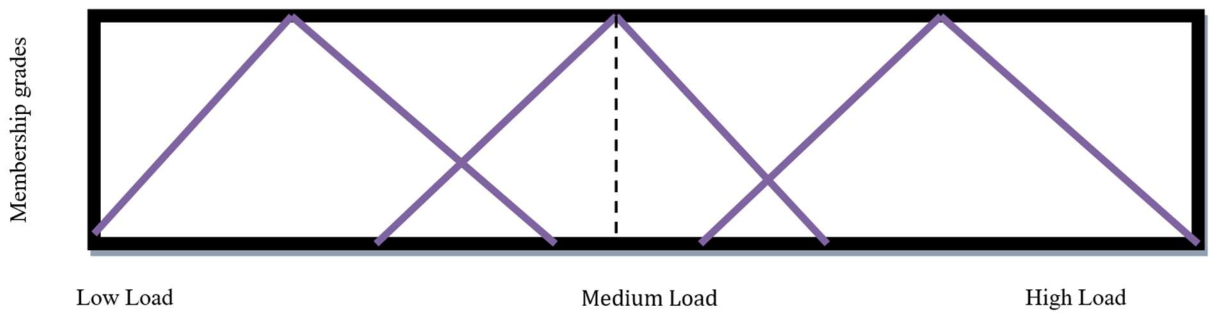


Fig. 5 Membership Functions

The fuzzy concept uses IF (condition) and THEN (termination) rules for connecting the input data (unscheduled demand data) with output data (i.e., low load, medium load and high load). The non-linear function is explained as,

$$FF \rightarrow \begin{cases} a = f(x) + g(x)w + H(x)v \\ b = \beta(x) \\ c = \alpha(x) + \varepsilon(x)w \end{cases} \qquad (8)$$

From (8), '$a \in R^{n}$', '$c \in R^{n_z}$', and '$b \in R^{n_y}$' symbolizes the state vector, controlled output and measured output. '$d \in R^{n_w}$' denote the variations in space. '$v \in R^{n_w}$' denotes control input. '$f(x), g(x), H(x), \alpha(x), \varepsilon(x), and\ \beta(x)$' denotes function of x.

Stochastic Selection

It is method of choosing the parent chromosome (i.e., time slot) for unscheduled load demands. Stochastic selection is carried out depending on the fitness selection. Stochastic selection uses the random time slots value to attain sampling of all solutions by selecting them at regular intervals. GFSRENL-OLS Model employed the stochastic function for selecting the best chromosome (i.e., time slot) based on fitness. The optimal time slots are identified with fitness function (FF). Threshold (T) is predefined to choose the best individuals in GFSRENL-OLS Model. An individual fitness below threshold is taken as parents for recombination task. Individual fitness higher than the threshold not generated offspring during recombination. Stochastic selection are formulated as,

$$SS = \begin{cases} FF \leq T\ ;\ Time\ Slot\ Selected \\ FF > T;\ \ Time\ Slot\ Not\ selected \end{cases} \quad (9$$

From (9), 'SS' represent the stochastic selection. 'FF' denotes the fitness function. 'T' represent the threshold. By this way, best individuals are selected for recombination process.

Ring Crossover: Crossover is method of managing more than one parent solution and producing offspring through swapping process. Ring operator carried out offspring generation from parent solution. Two parent chromosome 'm' and 'n' are described. It is formulated as,

$$time\ slot\ 1\ \rightarrow 101011$$
$$time\ slot\ 2\ \rightarrow 010011$$

Different time slots are joined to form the ring. The random cutting point is used at any position of the ring. The new offspring time slot is generated in clockwise direction. The other one is generated in an anti-clockwise direction. The offsprings (i.e., new time slots) are achieved through swapping of two existing time slots.

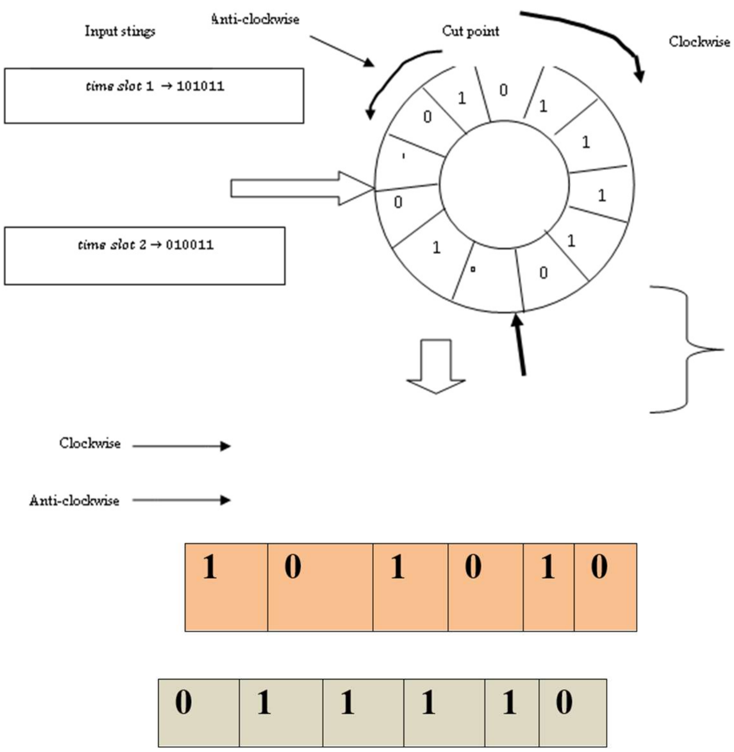
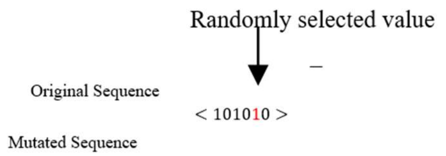


Fig. 6 Ring Crossover Process

As illustrated in fig. 6, ring crossover process is described to generate offspring . crossover is carried out based on mixture of two time slot solutions to provide the new adapted ones.

Mutation: Mutation changes one or more time slots from their initial state. In mutation, gene value is selected from the chromosome attained in the past generation and gene value is changed for generating new offspring.

Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4779-4795



$$< 101010 >$$
$$< 101000 > \quad (10)$$

From (10), the mutation sequence is attained in the original sequence. The red color symbolizes the randomly selected value for mutation in GFSRENL-OLS Model. The process gets repeated and the best global optimal time slot value is chosen.

// Genetic Fuzzy Swarm Optimization
Input: Number of unscheduled demands
Output: Optimal time slot
Step 1: Begin
Step 2: Generate an initial population
Step 3: Compute the fitness of unscheduled demands
Step 4: if fitness function is satisfied
Step 5: Select individual as optimal time slot
Step 6: else
Step 7: Perform Stochastic Selection
Step 8: Perform Ring Crossover
Step 9: Perform Mutation
Step 10: End if
Step 11: End

Algorithm 3 Genetic Fuzzy Swarm Optimization Algorithm

The *hidden layer 2 result* is expressed as

$$Hd(t) = \sum_{k=1}^{m} ED_k * w_{ini} + w_{h_1h_2} Hd(t-1) \quad (11)$$

From (11) '$Hd(t)$' symbolizes the output of hidden layer 2, '$w_{h_1h_2}$' represents the variable weight between hidden layer 1 and hidden layer 2. The process repeated to identify the time slot with minimal energy loss and energy consumption through using grid energy or renewable energy. The output layer of recurrent learning classification is computed as,

$$O(t) = Hd(t) * w_{oh_2} \quad (12)$$

From (12), '$O(t)$' represent the output layer. 'w_{oh_2}' denotes the weight between hidden layer 2 and output layer. By this way, an efficient energy management is carried out in smart grid based residential buildings.

5. SIMULATION RESULTS

Experimental evaluation of GFSRENL-OLS Model is implemented in the MATLAB Simulink. A simulation is carried out with for different parameters, namely PAR, Energy consumption, Load factor and Electricity costs.

Table 2 Tabulation value for Existing VAO Control Parameters

Population Size	Number of Clone	Number of Iterations	Crossover Probability	Mutation Probability	Lower and Upper Limit

Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4779-4795

30	30	1500	95	5	0 and 1

Table 3 Tabulation value for Proposed GFSRENL-OLS Control Parameters

Population Size	Number of Iterations	Crossover Probability	Mutation Probability	Lower and Upper Limit
30	1500	95	5	0 and 1

The above table 2 and table 3 explain the control parameters of existing VAO parameters and GFSRENL-OLS. The parameters such as PAR, Energy consumption, Load factor and Electricity costs describe performance of energy distribution in smart grid.

5.1 Impact of Electricity Cost

It is defined as amount of money charged for certain amount of electric power. electricity cost depends on electricity rate. It measured in cents per kilowatt-hour and formulated as,

$$Electricity\ Cost = \frac{Money\ charg}{Time\ period} \qquad (13).$$

Table 4 Tabulation for Electricity Cost at different hour

Time (hours)	Electricity Cost (Cent)
1	2.2
3	2.2
5	1.8
7	1.8
9	1.9
11	1.9
13	0.9
15	0.9
17	2.3
19	2.3
21	1.4
23	1.4

Table 5 Tabulation for Electricity Cost for Different Methods

Methods	Electricity Cost (Cent)
Unscheduling	6
Load shifting-based optimal demand-side management (DSM) model	5
Consensus algorithm-based coalition game theory	4

Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4779-4795

Proposed GFSRENL-OLS Model	1.75

The above table 4 and 5 explains the electricity cost of existing methods and proposed methods. When compared to the conventional methods, the proposed GFSRENL-OLS Model minimized the electricity cost.

5.2 Impact on Energy Consumption

It is defined as amount of energy consumed per unit time for performing efficient load shifting in smart grids at peak hours. It measured in kilo Watthour (kWh) and formulated as

$$Energy\ Consumption = \frac{Amount\ of\ energy\ consumed}{Time} \quad (14)$$

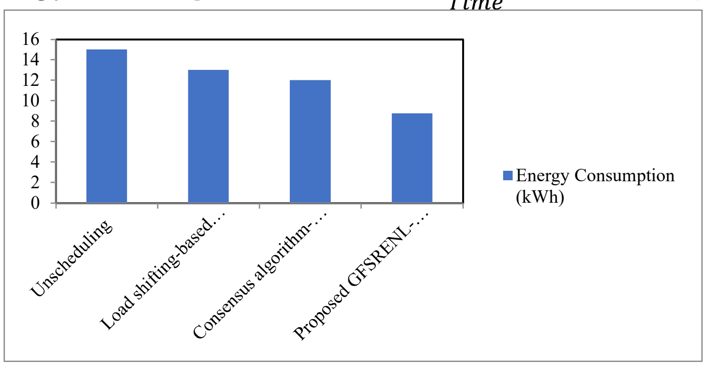


Fig. 7 Measurement of Energy Consumption

Fig. 7 explains the measurement of energy consumption. GFSRENL-OLS Model reduces the energy consumption. The energy consumption of GFSRENL-OLS Model is reduced by 33% and 27% than Load shifting-based optimal demand-side management (DSM) model and consensus algorithm-based coalition game theory respectively

5.3 Measurement of PAR

It is defined as difference in decibels between the peak and average levels of load demand. Load factor is inversely proportional to PAR.

Table 6: Measurement of Peak to Average Ratio for Different Techniques

Methods	**Peak-to-average Ratio**
Unscheduling	4.2
Load shifting-based optimal demand-side management (DSM) model	3.5
Consensus algorithm-based coalition game theory	3.1
Proposed GFSRENL-OLS Model	2.6

Table 6 describes the measurement of peak-to-average ratio. GFSRENL-OLS Model reduces PAR by 44% and 38% when compared to load shifting-based optimal demand-side management (DSM) model and Consensus algorithm-based coalition game theory respectively

4.4 Measurement of Load Factor

It is described as ratio of average load divided by maximum load in given time period. Load Factor is ratio of total energy (kWh) used over particular period of time to total energy available within period.

Table 7 Measurement of Load Factor for Different Techniques

Methods	Load Factor (Without RES)	Load Factor (With RES)
Unscheduling	0.23	0.23
Load shifting-based optimal demand-side management (DSM) model	0.58	0.99
Consensus algorithm-based coalition game theory	0.32	0.88
Proposed GFSRENL-OLS Model	0.38	1

The above table 7 explains the load factor of existing methods and proposed methods. When compared to the conventional methods, the proposed GFSRENL-OLS Model increased the load factor.

CONCLUSION

Our results demonstrate remarkable improvement with GFSRENL-OLS achieving a 30% reduction in energy consumption and 61% reduction in electricity costs when compared to existing methods.

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Catalyst Research Volume 23, Issue 2, December 2023 Pp. 4779-4795

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