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Enhancement of Distribution Transformer Lifespan by using Distributed Generation under Transactive Control Rescheduling

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Abstract: Due to the anticipated increase in loads, the power grid will encounter the issue of system peak loads in the future, which is typically addressed through grid reinforcement. However, implementing a flexibility service option can prevent the need for grid development. As the overall load continues to rise, the distribution transformer becomes overloaded. The presented work focuses on enhancing one of the parameters that define the insulation life of the transformer, known as the Loss-of-Life (LOL). Transactive approach involves the rescheduling of the battery and photovoltaic generation. Dominated Group Search Optimization (DGSO) algorithm is utilized to optimize the objective function of reducing the peak transformer load under the power flow and voltage constraints of the network. Experimental validation of the proposed method is conducted using MATLAB 2018 software. Modified IEEE 34-bus system is used to implement the proposed methodology. Numerical results obtained from various cases elucidate that the proposed model reduces the LOL of the transformer from 0.0103 to 0.0017p.u. Comparative analysis of the proposed method with the already used methods of voltage-control and Volt-Var control have been presented.

Keywords: Loss-of-Life, Power Distribution System, Insulation Life, transformer.

1 Introduction

THE use of Electric Vehicles is increasing daily, and it has been estimated that the number has nearly tripled from 2015 to 2020. Also, the predicted Solar PV units installed on the rooftop will get three times between 2015 and 2040 [1]. Residential battery storage systems will become 40 times approximately between 2016–2025 [2]. The application of battery storage systems is increasing due to the inability of Rooftop Solar PV and Electric Vehicle charging to coincide with the required capacity. A transactive energy control mechanism is required to benefit both the Distribution system and the end consumer/prosumer [3]. Transformer life degrades due to increasing count of the overloading of the transformer [4] [5] [6] [7] [8]. Generation from rooftop Solar PV cannot lower the transformer overloading due to the lower chronological coincidence between the EV charging and PV generation [9]. Also, studies in [10] [11] show that the Rooftop Solar PV generation can mitigate the transformer's loss-of-life due to the EV charging up to some extent. The work in transactive energy control uses power markets to link with the end consumers with a limited approach. Transactive control allows smart thermostats of the consumers/prosumers to bid in the real-time power market to reduce losses and maintain the system frequency [12] Also, the generation capabilities of the consumers improve with the inclusion of the Battery Storage system and Rooftop Solar PV systems through transactive control. The application of transactive energy allows the distribution company to control the consumer energy resources without many impacts on EV charging [13]. Transactive Energy System provides economic and social advantages to residential consumers having Battery

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Storage systems to reschedule their Battery System charging/discharging profiles. This, in turn, reduces transformer aging and total power losses [14].

Table 1 List of Abbreviations

Abbreviation	Definition
LOL	Loss-of-Life
DG	Distributed Generation
OLTC	On-Line Tap Changers
DGSO	Dominated Group Search Optimization
GSO	Group Search Optimization
VVC	Volt-VAr Control
EV	Electric Vehicle
RTS PV	RoofTop Solar PhotoVoltaic
BESS	Battery Energy Storage System
DSO	Distribution System Operator
NSRDB	National Solar Radiation DataBase
NREL	National Renewable Energy Laboratory
MINLP	Mixed-Integer Non-Linear Programming

1.1 Literature Review

The distribution sector requires an improved and flexible operation to accommodate the increasing number of distributed energy resources, as these cause power quality issues, reverse power flows, congestion problems, and voltage violations [15]. The Distribution system operator opts to expand the network for these reasons, but the grid extension requires cost and is not environment friendly. Demand Response programs are used as a distribution system in place of expanding the smart grid with demand flexibility [16]. Demand flexibility is generally applied for large-scale consumers, but small-scale consumers are also involved [17] Aggregator represents small-scale customers and manages the flexibility of operation in power markets [18]. A review of transactive energy systems and local energy markets is provided to ease the transactions in the regulated market [19] This novel market process must coordinate with the existing markets in the power sector to overcome the negative effects due to the flexibility provision [20]. The Demand flexibility mechanism in the energy market is developed in concept and definition, and not much work is done at the ground level; therefore, a Universal Smart Energy Framework (USEF) is proposed in [21] for designing various energy products and services, to improve the demand flexibility process. An optimization problem is initiated in [22] to accommodate the Distribution system operator's flexibility request. This problem is designed for an Aggregator, a Smart Energy provider, to manage various energy resources. A flexibility Clearing house is proposed in [23]to ease the integration of small-scale resources in the day-ahead market. This helps DSO mitigate the overload and voltage fluctuations along with the existing market operation. Flexibility services to DSO are based on the traffic light control system provided by De-Flex Market.

Work in [24] minimizes the operational cost and initiates a charging strategy for residential premises with transformer temperature as the constraint to reduce Loss-of-life. EV charging is done in the evening, and the impact of increased demand on transformer LOL in the presence of Rooftop Solar PV is [10]. The effect of EV charging at the residential level on the

life of the distribution transformer along with PV generation is considered in [25]. This study demonstrates the potential to extend the lifespan of transformers through optimal scheduling of electric vehicle (EV) charging [26]. The authors of this research investigate the feasibility of grid reinforcements from a cost and emissions perspective for an electrical network with high EV penetration. Their findings suggest that it is possible to reduce EV charging costs while staying within the current transformer capacity [27]. The article evaluates the impact of stochastic EV charging loads on the distribution network and concludes that such charging can lead to unacceptable voltage drops in load nodes. Due to the stochastic nature of EV charging loads, analytical modeling methods are impractical, and numerical methods are preferred [28]. The acceleration of distributional transformer aging resulting from additional charging loads from plug-in hybrid electric vehicles is evaluated in another study [29]. Probabilistic data-driven methods are presented to assess the severity of transformer overloading and aging when subjected to high levels of EV charging demand coupled with rooftop PV generation [30]. The authors of another article propose a deep learning approach based on a convolutional neural network to predict transformer lifespan [31]. The authors of two additional studies assess the loss of life (LoL) of transformers in distribution networks with individual residential houses and a high number of plug- in EVs. They investigate how transformer aging can be mitigated through power system reinforcement, including local PV generation and battery energy storage systems (BESSs) [32] and [33]. The results of one study indicate that the presence of PV generation in electrical networks with EV chargers can decrease transformer LoL, and with a BESS, this positive effect is even more significant [30].

The other segments included are as follows: Section II de- scribes the theory for transformer insulation aging. In

Section III, we described the methodology applied in this work. In Section IV, we described the experimental analysis and results. Finally, Section V concludes the study and discusses the future scope of the work.

2 Problem Formulation

2.1 Transformer Insulation Aging

Transformer is one of the essential and costliest equipment in the power system. Continuous operation of the transformer will increase its temperature. For this reason, the performance of distribution transformers will deteriorate early and cause the transformer to be replaced from use. IEEE Standard C57.91 proposed a model to predict the hot spot temperature of the transformer and its loss of life. As per IEEE standard C57.91 [8], the LOL of the transformer winding is directly proportional to the equivalent aging factor. The relation for Loss-of-Life is given in Equation (1).

$$LOL_W(\%) = \frac{F_{EQA} * t * 100}{L_N} \quad (1)$$

Where LOL_W is the transformer LOL for winding w, t is the time interval considered for evaluation, L_N is the normal insulation life of the transformer equal to 1,80,000 hours and F_{EQA} is the average equivalent aging factor, and is defined in Equation (2) as

$$F_{EQA} = \frac{\sum_{t=1}^{24} F_{AA}}{\sum_{t=1}^{24} \Delta T} * \boldsymbol{\Delta}\mathrm{T} \quad (2)$$

The average equivalent aging factor is defined as the average of the accelerated aging factor F_{AA}, given in Equation (3) as

$$F_{AA} = e^{\left[\frac{1500}{383} - \frac{1500}{\theta\_H + 273}\right]} \quad (3)$$

Accelerated aging factor is based on temperature θ_H, which is the temperature of the hottest point of the transformer, defined in Equation (4) as

$$\theta_H = \theta_A + \Delta\theta_{TO} + \Delta\theta_H \quad (4)$$

Where θ_A is the ambient temperature θ_{TO} is the temperature rise due to oil temperature and θ_H is the temperature rise due to winding IEEE C57.91 recommends that LOL_T is the Loss-of-Life of the winding of transformer which deteriorates the most, and is given in Equation (5) as below

$$LOL_T\ (\%) = \max LOL_w \quad (5)$$

Where W is the set of all transformer winding. It is assumed that normal aging occurs at 110^0C. If the temperature of the hottest spot exceeds 110^0C then F_{AA} will be greater than 1 and if its temperature is below 110^0C then F_{AA} is smaller than 1. For a 24-hour duty cycle, the F_{EQA} has a rating of 1.0 for continuous operation at maximum temperature. Therefore, the normal loss of life is one day every 24 hours. The range for severity of Equivalent Aging of transformer is given in Table 2.

Table 2 Severity range for various values of equivalent aging [34] [6]

Equivalent Aging range	Condition
$F_{EQA} < 0.95$	Insignificant
$0.95 < F_{EQA} < 1.0$	Moderate
$1.0 < F_{EQA} < 1.2$	Critical
$F_{EQA} > 1.2$	Severe

2.2 Modeling of the various loads

To include the secondary power line in the system, the house load profile, the RTS-PV profile, and the ESS profile are described below:

1. House Load Forecasting Model: The forecasting analysis utilizes the electricity demand data from Panama's power system, encompassing various demand variations including weekly, monthly, and yearly patterns. Additionally, it incorporates seasonal collections such as summer, rainy, and winter periods. The variability of data is assessed in terms of average and peak values. To mitigate the influence of noise and missing data, the data is subjected to transformation. The missing attributes are fulfilled by utilizing the average value of the data. Machine Learning techniques are employed to forecast the load.
2. RTS-PV Forecasting Model: Historical data gathered from the National Solar Radiation Database (NSRDB) of the National Renewable Energy Laboratory (NREL) is used to predict the temperature of each hour for the whole day.
3. Battery ESS: Battery considered in the analysis is Tesla Powerwall battery with a rating of 3.3kW,6.4kWh.

3 Proposed Methodology

3.1 Transactive Control Rescheduling

As the load on the transformer increases, transactive energy plays a significant role in minimizing the load on the transformer and prolonging its life. The load is estimated every hour using a machine learning algorithm to take the load of the transformer for 24 hours instantly [35]. When the peak load of the transformer increases by more than 1p.u., the Transactive mechanism adjusts the load. In this work, we analyze the benefits of the transactive control for improving the life of the transformer by evaluating the loss-of-life (LOL). The flowchart for the overall methodology used is shown in Fig.1.

For the Transactive control method to be effective, the DSO proposes an offer to the consumer/prosumer to act (PV and battery scheduling) that will ultimately be accepted or rejected. For the ultimatum game, the buyer's (here, the consumer's) the best strategy is to get an offer whose value is greater than or equal to its present value. In this context, all customers determine the economic value of their ESS price/discharge or PV output to the grid, like their electricity costs.

The expected outcomes of this study include achieving optimal control of batteries and photovoltaic (PV) systems, leading to minimized transformer aging, by maintaining optimal voltage levels and power flows.

3.2 Algorithm Applied

The Dominated Group Search Optimization (DGSO) algorithm is an improved version of the traditional Group Search Optimization (GSO) algorithm, specifically designed to address complex mixed-integer nonlinear programming (MINLP) problems more efficiently. In the GSO algorithm, the population is categorized into three types: producers, scroungers, and rangers. Producers are the members with the highest fitness levels, responsible for exploring nearby regions in the search space to identify better solutions. Scroungers follow the producers, using the information provided by them to efficiently exploit the search space, thereby refining the search and enhancing optimization. Rangers, however, perform random searches across the search space, exploring new areas to potentially discover better solutions. The movement of rangers within the search space is governed by a specific equation that determines their path and behavior. The equation governing this is given below as Equation (6).

$$R_i^{k+1} = R_i^k + l_i D_i^k \emptyset^{k+1}, \; l_i = a \times r_1 \times l_{max} \qquad (6)$$

where R^k and D^k are the position and direction of i^{th} ranger in the k^{th} iteration, respectively. Moreover, ϕ represents the random head angle. In addition, l_i is the produced random distance.

The DGSO algorithm introduces enhancements that focus on optimizing the behavior of the scrounger members within the group, which are crucial for the convergence and efficiency of the optimization process. DGSO takes into account the distance of scroungers from the producer. Scroungers that are closer to the producer are more likely to follow. This approach involves classifying scroungers based on their proximity to the producer, allowing for more informed decisions about whether they should follow the producer or continue their random search. To this end, after performing the producing and ranging actions, the available scroungers are divided according to their distance from the producers. Afterwards, each scrounger is prepared to approach to the nearest producer as described in Equation (7).

$$X_{s,i}^{K+1} = X_{s,i}^{K} + r^0 \left|(X_P^K - X_{s,i}^K)\right|, \left|(X_P^K - X_{s,i}^K)\right| < \left|(X_{pR}^K - X_{s,i}^K)\right|$$

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Where X_P^K and X_{pR}^K are the producer and the producer of rangers in k^{th} iteration, respectively. On the other hand, $X_{s,i}^{K+1}$ and $X_{s,i}^K$ represent the position of i^{th} scrounger during two consecutive iterations. $r \in R^n$ is a uniform random number which is always in the range (0,1). This refined tracking mechanism enhances the overall accuracy of the search process, facilitating more effective exploitation of high- quality solution areas.

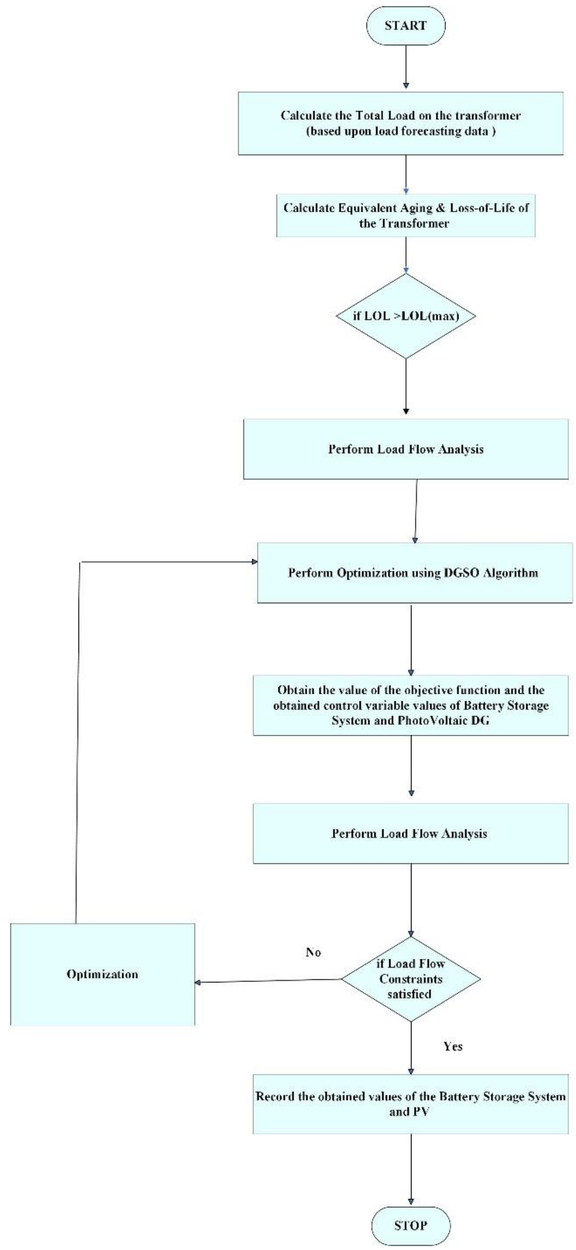

Fig. 1 Methodology Flowchart

3.3 Mathematical formulation

The transactive control optimization process begins by inputting system data into the algorithm. Initially, load flow calculations are performed to establish a baseline setup. The results from these calculations are then fed into the DGSO algorithm, which evaluates the system's objectives and constraints. In applying the DGSO algorithm to optimize a power distribution system transformer's Loss of Life (LoL), typical control variables include the battery output power and PV output power. The DGSO algorithm iteratively adjusts these control variables to minimize the objective function of reducing transformer aging while adhering to system constraints. This iterative process is repeated, continuously refining the control variables, until the primary objective of minimizing transformer aging is achieved.

To reduce the maximum power, the estimated load for each hour is calculated using the forecast as described in Equation (8) ,where P_T^t is the active power load for the transformer T for the time instant t of a T duration , P_h is the house load power, P_t is the power produced in RTS-PV and P_{PV}^t, $\sum_{ess\ \varepsilon\ ESS} P_{ESS}^t$ is the battery storage system power.

$$P_T^t = \sum_{h\ \varepsilon H} P_h^t - \sum_{p\ \varepsilon PV} P_{PV}^t + \sum_{ess\ \varepsilon\ ESS} P_{ESS}^t \tag{8}$$

In this study, it is assumed that all consumers with ESS/PV use their ESS/PV to reduce the electricity bill. To reduce the aging of the transformer by Transactive control, DSO will bid for all customers using ESS/PV to reduce the load on the transformer. DSO sends the offer to the customer to reschedule the ESS/PV output as per the amount of load on the transformer, to reduce the transformer peak load [60]. Consumers aim to use PV locally (net metering) to earn electricity bill profit rather than selling it to the grid (gross metering). The objective of the consumer is to lower the consumer's monthly electricity bill, as described in Equation (9). Charging/discharging of the battery and PV selling is considered, as the rest of the component in the residential load is identical in all the cases.

$$C_e = \sum_{t=1}^{T} C_t^P \, P_t^{BESS} \, \boldsymbol{\Delta}\mathrm{T} \tag{9}$$

C_t^P is the price of the unit electricity (Rs. /kWh) to charge battery. T is the total time taken, aT is the time duration considered and P_t^{BESS} and E_t^{BESS} is the charging/discharging power and energy of the battery for time 't'. The above function is subject to the constraints of the battery storage system, as given in Equations (12) and (13).

The objective function is to minimize the equivalent aging of the transformer. This is expressed as a non-linear function subject to operational constraints. The control variables, battery power, and PV output power are integer types, making this a mixed-integer non-linear programming (MINLP) problem. The function can be mathematically formulated as given below in Equation (10).

$$\text{Min f} = \frac{Max\ (P_{trans})}{P_{avg}} \tag{10}$$

Where P_{avg} is the average power for the whole day of operation, defined in Equation (11) below as,

$$P_{avg} = \frac{\sum_{t=1}^{T}(P_{trans,t})}{T} \tag{11}$$

Where $P_{trans,t}$ is the power output of the transformer at hour 't'.

This objective function is subject to the following constraints of Energy, Power and voltage given in Equations (12), (13), (14) and (15).

$$P_{min}^{BESS} < P_t^{BESS} < P_{max}^{BESS} \tag{12}$$

$$E_{min}^{BESS} < E_t^{BESS} < E_{max}^{BESS} \tag{13}$$

$$P_{trans,min} < P_{trans,t} < P_{trans,max} \tag{14}$$

$$V_{min} < \mathrm{V} < V_{max} \tag{15}$$

Where E_{max}^{BESS} , E_{min}^{BESS} , P_{max}^{BESS} , P_{min}^{BESS} are the energy and power constraints for the battery system. V_{min}, V_{max} are the power flow voltage limits (Normally 0.95 <V<1.05 p.u.). $P_{trans,max}$, $P_{trans,min}$ are the power output constraints of the transformer.

4 Experimental Analysis and Results

MATLAB software is utilized for time-series simulations of load flow in the system. To compute kVA flowing through the transformers of the distribution system, load flow studies has been carried out in conjunction with the optimization routine. Key data concerning the distribution system, including transformer data, load data, line data, and capacitor data, are input into the algorithm. All load flow calculations are conducted and the results are subsequently fed into the DGSO algorithm, which assesses the necessary objectives and identifies any constraint violations. Based on the evaluated objective value, the control variables are updated for the next iteration. This iterative process continues until the desired objective is achieved. Load flow analysis is conducted with a sampling interval of one hour over a 24-hour period.

4.1 Modified IEEE 34-bus System

IEEE 34-bus system is modified and is used for simulation. The feeder's nominal voltage is 24.9 kV. It is characterized by 3-phase 4-wire and single phase, 2-wire overhead lines arranged in different configurations. Two in-line regulators are required to maintain a good voltage profile. Unbalanced loading with both "spot" and "distributed" loads are present. Distributed loads are assumed to be connected at the center of the line segment.

Node no.33 with a spot load rating of 22.36kVA is modified and replaced with a transformer of 25kVA rating. This transformer extends and connects six houses, as shown in Figure 2 [7]. Each house contains an average house load, one Solar PhotoVoltaic generator (PV), and one Battery Energy Storage System (ESS). The ratings and specifications of the Battery are 6.4 kWh (energy), 3.3 kW (peak power), and 2 kW (continuous power), and that of PV are 10 kW (Output power),120 V (output voltage). Residential house loading is assumed 6.64kVA at each house.

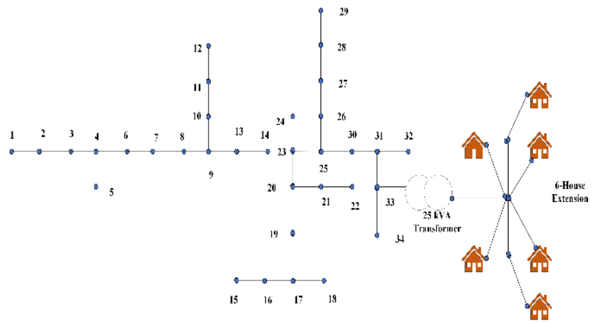

Fig. 2 IEEE 34 bus system

The efficiency of the design is analyzed by considering various combinations of photo voltaic generation and battery storage systems, as described in further section.

4.2 Transformer Loading For various cases

Case I: Base Case without Transactive Mechanism (No PV No Battery): The load on the transformer for each hour for a 24-hour duration is forecast using machine learning, and their equivalent aging hours are given in Table 2. This case is considered the base case as no transactive control is applied here.

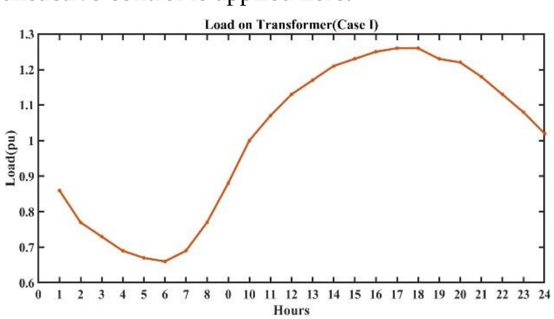

Fig. 3 Load on transformer Case I

Case II: With Battery and PV for Peak load reduction Transactive Mechanism: The transformer loads for each hour for a 24-hour duration, and then transactive control is applied to reduce the peak load on the transformer; their equivalent aging hours are given in Table 2. This is the second case where RTS-PV and battery are used in transactive control to minimize the peak load of the transformer. Here peak loading for 6 pm is reduced using transactive control. As the peak load is reduced, the equivalent aging reduces and finally the Loss-of-life of the transformer gets reduced.

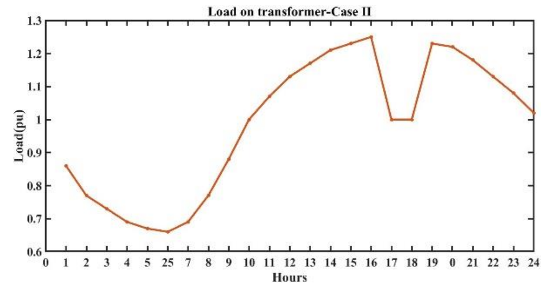

Fig. 4 Load on transformer Case II

Case III: With Battery and PV for Overload reduction Transactive Mechanism: The transformer loads for each hour for a 24-hour duration, and then transactive control is applied to reduce the overload on the transformer; their equivalent aging hours are given in Table 4. This is the third case where RTS-PV and battery are used in transactive control to minimize the overload on the transformer. Here overloading between 2 pm to 8 pm is reduced using transactive control. As the load is reduced, the equivalent aging reduces and eventually the Loss-of-life of the transformer gets reduced.

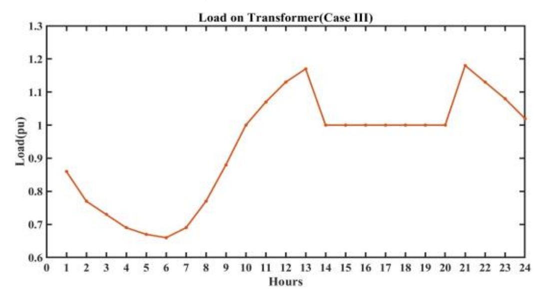

Fig. 5 Load on transformer Case III

Case IV: Use of Battery only for Transactive Mechanism: The transformer loads for each hour for a 24-hour duration, and then transactive control is applied to reduce the overload/peak load on the transformer; their equivalent aging hours are given in Table 2. This is the fourth case where only the battery is used for transactive control optimization. Here the load on the transformer is adjusted with the help of a battery storage system. When the load on the transformer is on the lower side, the battery is charged and discharged when there is a need for more power to supply to the loads. As the load is reduced, the equivalent aging reduces and then the Loss-of-life of the transformer gets reduced.

Based on the methodology presented in subsection**,** and objective function, the value of DG powers for Battery Storage System and Solar Photo voltaic have been evaluated. The CPU time and convergence characteristics are the important factors to indicate robustness of any algorithm. The number of generations considered in the study are 200. The mean CPU time to converge the solution in different case were 2.3×104s, 1.95×104s, 1.73×104s, and 1.61×104s, respectively.

Table 3 Load on transformer and the corresponding aging acceleration for various cases

Hour	Case I p.u. load	Case I Aging Acceleration	Case II p.u.load	Case II Aging Acceleration	Case III p.u.loading	Case III Aging Acceleration	Case IV p.u.loading	Case IV Aging Acceleration
1	0.86	0.2026	0.86	0.2026	0.86	0.2026	1	0.0577
2	0.77	0.0819	0.77	0.0819	0.77	0.0819	1	0.0577
3	0.73	0.0404	0.73	0.0404	0.73	0.0404	1	0.0577
4	0.69	0.022	0.69	0.022	0.69	0.022	0.96	0.0513
5	0.67	0.0134	0.67	0.0134	0.67	0.0134	0.94	0.0455
6	0.66	0.0091	0.66	0.0091	0.66	0.0091	0.93	0.0455
7	0.69	0.0091	0.69	0.0091	0.69	0.0091	0.96	0.0513
8	0.77	0.0118	0.77	0.0118	0.77	0.0118	1	0.0577
9	0.88	0.022	0.88	0.022	0.88	0.022	1	0.0577
10	1	0.0577	1	0.0577	1	0.0577	1	0.0577
11	1.07	0.1295	1.07	0.1295	1.07	0.1295	1.07	0.1295
12	1.13	0.2526	1.13	0.2526	1.13	0.2526	1	0.0577
13	1.17	0.4823	1.17	0.4823	1.17	0.4823	1	0.0577
14	1.21	0.9026	1.21	0.9026	1	0.0577	1	0.0577
15	1.23	1.499	1.23	1.499	1	0.0577	1	0.0577
16	1.25	2.2285	1.25	2.2285	1	0.0577	1	0.0577
17	1.26	2.9845	1.26	2.9845	1	0.0577	1	0.0577
18	1.26	3.6172	1.26	3.6172	1	0.0577	1	0.0577
19	1.23	3.2865	1.23	3.2865	1	0.0577	1	0.0577
20	1.22	3.2865	1.22	3.2865	1	0.0577	1	0.0577
21	1.18	2.4576	1.18	2.4576	1.18	2.4576	1	0.0577
22	1.13	1.8296	1.13	1.8296	1.13	1.8296	1	0.0577
23	1.08	1.1074	1.08	1.1074	1.08	1.1074	1.08	1.1074
24	1.02	0.6614	1.02	0.6614	1.02	0.6614	1.02	0.6614
Aging Acceleration total		25.1952		18.7089		7.7943		3.0728
Equivalent Aging		1.0498		0.7795		0.3247		0.128
LOL		0.0139		0.0103		0.0043		0.0017

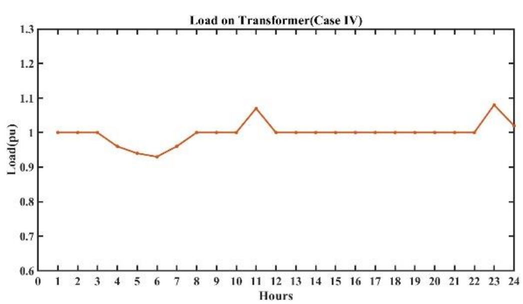

Fig. 6 Load on transformer Case IV

The total loads supplied by the transformer for all four proposed cases are shown in Figure 3 and Figure 4. Here Table 2 presents the summary of equivalent aging, daily loading and LoL. Base-case results in extensive aging of the transformers. It can be seen that there is a significant reduction in the aging acceleration in the transformer in Case IV. The loading of the transformer is shifted nearer to its rated capacity (Case IV). Since, the aging acceleration factor varies exponentially with hottest-spot temperature, there is a considerable reduction in aging of the transformer. The daily equivalent aging for life of the Distribution Transformer for the four cases, base-case, transactive peak load control, transactive overload control and transactive battery rescheduling control are 0.7795, 0.3247, and 0.128, respectively.

The hottest-spot temperature variations have a different trend as compared to the transformer loading curves.

This is due to the fact that loading is a function of voltage and current, whereas temperature rise is the function of current only. Effect of any type of control is more prominent when load supplied by the transformer increases above its rated capacity. With transactive control, there is a substantial reduction in aging acceleration throughout a day for all the cases. It can be seen that the losses inside the transformers are greatly affected by the type of Transactive control strategy. The transactive control results in a more economical solution from the point of view of Distribution Transformer aging.

4.3 Comparison of proposed method with existing techniques

There are several existing methods for the reduction of LoL of the distribution transformers. These methods are described below:

1. Voltage Control: In this case, voltage control devices such as On-Line Tap Changers (OLTC) and Regulators are operated such that the objective of transformer overload/peak load reduction is satisfied.
2. Volt-VAr Control: In this case, in addition to voltage controlling devices, the capacitors connected in the system are also controlled to optimize voltage and VAr flow in the system to

minimize the objective function without violating the system constraints.

3. Transactive Control: In this method, transactive control rescheduling of the Distributed Generation (DG) is used to minimize the objective function of transformer loss of life considering the system constraints, as already discussed. Due to optimal control of DGs, the loading is least in the case of Transactive Control.

A comparative analysis of the LoL of a transformer using the transactive control optimization with already existing methods in terms of aging acceleration, equivalent aging and LOL is summarized in Table 3.

The results indicate that effect of Transactive Control, on the LoL of the transformer, is more prominent as compared to base-case, voltage control and volt-Var control cases. It is ascertained that the optimal Transactive mechanism results in significant reduction in aging rate of the Transformer.

Table 4 Comparison with other existing methods [36]

S.No. /Scheme	Voltage Control	VoltVar Control	Transactive Control Case II	Transactive Control Case III	Transactive Control Case IV
Aging Acceleration	70.008	45.36	18.708	7.7928	3.072
Equivalent Aging	2.917	1.89	0.7795	0.3247	0.128
Transformer LOL	0.0388	0.0252	0.0103	0.0043	0.0017

5 Conclusion and Future Scope

The transactive control mechanism for distribution system is described in the work involved. This scheme improves the distribution transformer life span by reducing the load over the transformer for a particular duration. Battery energy storage and PV systems are applied in control schemes to balance the surplus and deficit amount of power, to reduce the Loss-of- life of the transformer within the permissible limits. Various combinations of battery energy storage systems and PV power are considered to show the effectiveness of the applied scheme. The proposed methodology is validated on modified IEEE 34- bus system with various load profiles.

Conflict of Interest

We declare that we 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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