A Novel Coordinated Voltage Stabilizing and Load Scheduling Algorithm for Smart Grids

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***Abstract*— Due to growing use of advance metering infrastructure (AMI), and advance communication technologies, optimization of the utility grid has become easy and fast, which has increased the overall power delivering efficiency of the grid and minimized the per unit cost. Moreover, this technological advancement has also enhanced the voltage fluctuations controlling capability of a grid, introduced by the intermittent resources. This paper proposes a power flow analysis technique to suppress the abrupt voltage variations introduced by renewables in a decentralized power network. To simultaneously reduce the energy consumption cost along stabilizing voltages in a decentralized network, a consumer-grid relation-based load scheduling technique is being proposed, which concurrently changes the VR tap position for load scheduling according to the consumers' load demands for multiple time slots. Performance of the proposed techniques are verified by comparing the results with conventionally used algorithms. Intense performance evaluation proved the proposed model can significantly minimize the electricity generation cost, efficiently perform load scheduling and effectively stabilizes the voltage fluctuation constraints in a decentralized power network.**

Index Terms*— *Demand Side Management, Decentralized Network, Distributed Generation, Renewable Resources, Voltage Regulator. Advance Metering Infrastructure.

NOMENCLATURE

T	Total time period.
$l_{k,t}$	Load of k household at time t
L_t	Vector for load scheduling for each household.
$\mathcal{R}$	Set of decentralized renewable resources.
E_t	Total produced electricity during time $t \in T$.
$e_{r,t}$	Generated Electricity by r during time t.
N_{Total}	Total number of households.
$\mathcal{N}$	Total numbers of households in operation.
$\mathcal{N}_f, \mathcal{N}_{nf}$	Total number of flexible and non-flexible load consuming appliances.
$\mathcal{H}_k$	Anticipated on time duration of each household$t \in \mathcal{N}_v$.
$L_{f,t}, L_{nf,t}$	Total load of flexible and non-flexible power consuming appliances.
$P_{k.Low}, P_{k.High}$	Lowest and highest power consumed by an appliance k at time t.
$\mathcal{P}_{k,On}$	Minimal energy required to power an appliance k to accomplish a given task.
$\mathcal{B}$	Total number of buses.
$\mathcal{N}_{k,On}$	Number of appliances being fed by bus b_k
$\mathcal{R}_{k,Total}$	Number of DGs connected with b_k.
$V_{b1}(t), V_{b2}(t)$	Voltage comparison of two adjacent buses at time t.
$P_{k,b}(t), \mathcal{Q}_{k,b}(t)$	Active power and reactive power flow between buses at time t.
$P_k(t), \mathcal{Q}_k(t)$	Injected active power and reactive Power at bus b_k at time t.
$D\mathcal{R}_{k,t}$	Injected power from various distributed renewable at each bus b_k.
V_{low}, V_{high}	Lowest and highest voltages limitation of each bus.
V^*	Nominal voltages of decentralized network.
$\mathcal{X}$	Number of tapings of a load tap changer (LTC').
$v \in \mathcal{V}$	Corresponding voltages of bus b_0.
$x_t \in \mathcal{X}$	LTC' changed position at time t.
c_t	Per unit cost of electricity at time t.
C_e	Total cost of generated electricity.
$\mathcal{P}, \mathcal{F}$	Results of (DP') and (PP').
λ, s	Lagrange multiplier matrix.

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I. INTRODUCTION

From past few years, consumer load on the conventional power grids is consistently increasing. Service providers in several areas of the world are unable to supply continuous and reliable power to the consumers. Therefore, it is imperative to upgrade conventional power grid to smart grid by the intelligent integration of renewable resources, and by upgrading old communication infrastructure. Hence a conventional grid could be upgraded to Smart Grid (SG). SG enables load scheduling and real time monitoring of electric loads, which helps in supplying constant and reliable electricity supply to the consumers, for instance by penetrating smart metering infrastructure and advance communication network, grid optimization could become easy and robust [1]. The real time dispatched power monitoring also enables the load shifting from peak hours to off-peak hours, after considering consumers' preferences. Several Demand Side Management (DSM) or Demand Response (DR) techniques have been developed in literature to efficiently govern the load shifting processes [2]. Several studies proved that the load scheduling is an effective method and could be used for reducing load in peak hours, it minimizes the energy procurement cost, and reduces the need of new power plants. These incentives make SG a feasible solution for smart city's energy management. In addition, the emerging threat of global warming has also compelled nations across the globe to reduce Greenhouse Gas (GHG) emissions by constructing new renewable power generation plants (e.g., photovoltaic and wind power plants) which are now considered as efficient way of clean energy generation. A report prepared by International Energy Agency (IEA) states that energy production from renewable sources will be tripled by the year 2035, it would have overall 32% share of the global power production. This study anticipates that till

2035, the photovoltaic and wind power plants will generate about 27% and 5% of the total renewables production, respectively [3, 4]. In SG, the system frequency is maintained with the help of primary and secondary load controlling methods. i.e., vehicles to grid system enables the penetration of Electric Vehicles (EVs) as energy storage devices, which could be used as instantaneous grid stabilization tool. The propagation of renewable power plants comprises higher proliferation of clean energy generators and decentralized energy storage platforms i.e., integration of distributed battery storage systems and EVs, provide several implementable options for grid stabilization in peak hours. Although, the integration of intermittent power generation resources provides clean energy, but due to increased renewable penetration, load scheduling has become compulsory in a SG to cope with voltage fluctuation problems. In an isolated electric grid, where frequency deviations are high, EVs might be used as a primary frequency controller, it may enhance the stability of power grid.

Each renewable resource exhibits stochastic and intermittent nature; therefore, their power generation is not constant, which can cause under rated or overrated voltages [5, 6], and usually makes load regulation very difficult. An efficient way to overcome these difficulties is the anticipation of real-time electricity production profile of distributed power generators. This method could be used to optimize the voltages on network buses by using the energy stored in EVs, which can stabilize the voltage in a tolerable limit [7]. It has been analyzed that, a grid with high renewable resources faces sever voltage fluctuations and load regulation constraints. To cope these constraints, and in order to maintain the constant voltages on the distribution lines, the voltage regulators (VRs) are installed to even out uncertain voltage variations on different network buses by altering the VR tap, hence stable voltages are maintained on a network bus. For example, the voltages on different feeders can be managed by 10% buck to 10% boost voltages by using the McGrew-Edison-single-phase VRs technique [8]. Since insufficient available power and wrong VRs tap selection can collectively cause voltage transients and fluctuations in SG, therefore, the voltage stabilizing schemes must be precisely selected by efficiently coordinating the load scheduling schemes.

In past two-decades, massive research work has been carried out to efficiently stabilize load on the utility grids where renewables are the main source of energy generation. In addition, in order to minimize the peak to average ratio (PAR) between supply and demand, or to produce economical electricity several algorithms have been proposed in literature [8]. However, some of the existing techniques cater the voltage transients by employing load scheduling techniques, which collectively reduce the energy prices and regulates the stochastic voltage transients but failed to stabilize voltages of the commercial grids. In this paper, voltage regulation problem is being proposed, which efficiently schedules the load in a decentralized network. It efficiently integrates several renewable recourses in a utility grid and successfully suppress voltage transients. Moreover, a grid aggregation method is also proposed, which collaborates both grid and consumers' partnership, reduces the total energy cost and it also regulates the voltages in a DG network. This paper contributes to the literature in the following manners:

1. In a decentralized power network by using the load flow analysis, the voltage transients produced by the renewables are considered as a load regulation constraint. For this purpose, a voltage regulation method has been proposed to stabilize voltages at each network bus which eventually coordinates the load stabilization process in a synchronized manner. The voltage stabilization has been achieved by optimally changing the tap of the voltage regulators. To reduce the overall energy procurement price, the following constraint is formulated as the Mix-integral-nonlinear-programming (MIMLPs) constraint, this MIMLP problem is further expanded into two sub problems. In last the original load regulation problem has been solved by computing these sub-problems independently and separately for achieving optimal voltage stabilization.

2. After acquiring the optimal solution for the original voltage stabilizing problem, load scheduling algorithms have been proposed for online and offline consumers load scheduling, which enable the consumer to change the voltage regulator taps according to the energy produced by renewables, voltage transients and power demand. For online consumers, an online algorithm is developed using 4G communication network for broadcasting instructions to perform load scheduling tasks. "*Online Algorithm*" can define the separate schedule for load optimization during each time slot, considering real time power production cost, network information, and current ecological conditions. In last, extensive performance evaluation has been carried out by numerical analysis, evaluated by comparing the actual renewable power generation and consumption statistics with the conventionally used Deng's algorithm. The designed strategy performs efficient load scheduling and regulates voltage fluctuations effectively, it considerably minimizes the power procurement cost and stabilize voltages in a decentralized network.

The paper is arranged as follows, Section II covers the literature survey, Section III, covers the system model. The detail of simultaneous voltage regulation problems formulation and load scheduling scheme is given in Section IV while Section V covers the solution analysis, respectively. An aggregator for load scheduling coordination between consumers and gird is developed in Section VI. The Section VIII shows the performance evaluation results of the proposed model. In last, the conclusion and outlined future work of this paper is given in Section VIII.

II. LITERATURE SURVEY

Due to the consistently growing load on the conventional grids, the effectiveness of load scheduling methods has significantly emerged in past few years. Particularly relevance of load optimization has been proved in minimizing peak to average ratio (PAR) difference between demand and supply, it has also enabled the broader renewable integration for producing economical electricity. It also allows the direct or indirect load controlling, according to the defined controlling mechanisms [6-9].

In SG the consumer load is controlled remotely by a central aggregator office, which is responsible of regulating load of each individual consumer. This central load optimization is usually carried out on those locations where the demand is comparative low i.e., residential areas, by applying the load scheduling strategies. In [10], a load leveling scheme for residential consumers has been proposed to reduce the energy cost for consumers; satisfactions. This scheme can determine the optimal scheduling even if the communication between consumer and service providing company is restricted or completely lost. In ref [11], the local load scheduling constraint is addressed by penetrating the game theoretical scheme which considers the consumer's power consuming preferences. Moreover, some authors studied to extend this approach for commercial deployment using demand response in smart grids. Shen at. al, developed an adoptive load diverting algorithm to reduce the computational load on the utility grid besides energy cost minimization, reliable power supply is assured [12]. Meanwhile, with the propagation of renewables and electric vehicles (EVs), the energy generation forecast, and elastic energy storage scheduling have been incorporated for demand management in SG. In ref [13], authors proposed a centralized scheme for simultaneous load scheduling of household appliances and plugged-in EVs to reduce the energy expenditures for consumers. In ref [14], the effect of EVs has been analyzed in a local grid and demand side management scheme is developed as a load stabilizing tool to cope with the transformers overloading.

The distributed load management framework aims to economically satisfy consumers, by making them independent load controllers, through dynamic cost adjustments. In [15] author proposed an instantaneous cost adjustment strategy, jointly working with the optimization algorithm to stabilize consumer load in hourly slots according to the defined electricity price for each separate time slot. Various comprehensive research studies have also been carried out to analyze the constraints during determination of the energy price for different hourly slots, for instance, local renewable energy production [16], and consumers' fairness [17]. For instance, a real time energy price determination scheme is proposed in [16] to assist higher renewables penetration by enabling load elastically for load stabilization. In [17], an adoptive load scheduling for PHEV battery exchange strategy (same for BES) has been proposed. The objective of this proposed model was to check the impact of unreliable data communication on the load scheduling tasks, but in this study BES contribution to the DSM system is not analyzed. The objective of this paper is based on BESs analysis, rather than focusing on direct PHEVs charging. In [18], author emphasizes that fairness is essential when generated revenue is paid to the consumers according to their contribution in network optimization. Therefore, in this paper, an autonomous billing scheme is developed to ensure both fairness and optimality in demand side management. In [19], researcher created a Stackelberg game for creating coordination between customers and service providers, where energy suppliers act as leaders and tend to enhance their overall reserves (profit margin). While, customers behave like followers and dynamically govern the load scheduling for whole network.

To practically implement the load scheduling approach, several studies particularly focus on the voltage stabilization in SG, where selection of accurate VR taps is required to stabilize the voltage transients caused by the distributed generators. In [20], an optimization model for the distributed generator voltage regulation has been proposed which jointly reduces the energy loss in a power network and automatically selects the tap positions of different VRs according to load on network buses. In [21], a decentralized voltage regulating model has been proposed to reduce the "Active Power, loss as well as the overall "Reactive Power" procurement in low rated networks interconnected with radial topologies, for higher loads the live-VR tap controlling is adopted to further minimize the overall power loss. In [22], authors evaluated energy loss in a distributed power network due to sever voltage fluctuations and reverse flow of power, under broader scale DG penetrations. In this paper author has structured a decision rendering algorithm to perform the optimum load scheduling for a distributed generation system comprising battery storage system, load controlling and taping transformers, to reduce power losses.

Although, some existing techniques simultaneously consider load scheduling and voltage fluctuation issues to regulate energy price in a power grid, which are highly complex to jointly compute, and failed to integrate various renewable resources in a decentralized power network. However, numerous researchers tried to investigate the voltage stabilization and regulation issues, consistently occurs in a power system [5,23]. However, despite these efforts no considerable achievement has been reached in efficiently performing load scheduling to regulate system voltages during maintaining the required power flow. Therefore, in this paper, a simultaneous load scheduling, and nominal voltage regulating constraint is proposed to efficiently adjust the VRs and to simultaneously govern load scheduling on multiple buses, to minimize the energy cost as well as to achieve optimal voltage regulation and stabilization.

III. System Modelling

Infer a decentralized power network, comprises, a set of renewable distributed generators $\mathcal{R}(|\mathcal{R}| = R)$, a central management authority, and a combination of households $\mathcal{N}(|\mathcal{N}| = N)$. This managing authority is responsible for controlling and scheduling the power demand of household appliances, and jointly optimize the VR operations to optimally connect VRs with different network buses. Each distributed generator comprises a remote terminal unit (RTU) for broadcasting data to the central managing office. Each household is intelligently connected to the smart meter by Zigbee or Bluetooth. These smart meters are capable of exchanging data with the central office in order to regulate the working time of each household. In addition, a day has been divided into multiple time slots (i.e., 24) presented by $\mathcal{T}[1, \dots, T]$. To represent each decentralized renewable generator (DG) $r \in \mathcal{R}$. let $e_{r,t}$ is the power produced by r during time t, while the total produced power during the time duration $t \in \mathcal{T}$ is $E_t = \sum_{r \in \mathcal{R}} e_{r,t}$. In this renewable generation modelling, I have assumed the photovoltaic plants and wind turbines are main source of power generation. Note, these renewable resources exhibit stochastic nature, however various already developed models can anticipate the short-term power production by renewable resources precisely but failed to forecast power production statistics on commercial level [16].

A. Consumer Load Modelling

The consumer load has been divided into two different categories flexible load and non-flexible. The superscripts $\mathcal{N}_f$ and $\mathcal{N}_{nf}$ show the total number of flexible and non-flexible households. The combination of overall household appliances is represented by $\mathcal{N} = \mathcal{N}_f \cup \mathcal{N}_{nf}$. For a time instance t, variables $L_{nf,t}$ and $L_{f,t}$ denote the total load of non-flexible and flexible households, while L_t is the total load of all households, and it could be computed by $L_t = L_{nf,t} + L_{f,t}$.

For each household $k \in \mathcal{N}$, infer $l_{k,t}$ is the total load of a k household at time t. Note, the non-flexible load of a household could not be diverted, therefore $l_{k,t}$ is assumed as a fixed load for each non-flexible appliance as $k \in \mathcal{N}_{nf}$ and each $t \in \mathcal{T}$. Conversely, the flexible loads of household appliances $\mathcal{N}_f$ (i.e., Clothing dryers and EVs) could be diverted and scheduled by the central office to achieve the optimal power flow. In this power network, consumers are only concerned with the accomplishment of assigned tasks. [12,16]. Let $a_{k,t}$ is the defined schedule for load shifting of each household $k \in \mathcal{N}$ at time t, thus $l_t \triangleq \{l_{k,t}\} k \in \mathcal{N}_f$ show the vector of load scheduling for each flexible household appliance during time t, and $A \triangleq [l_t]_{t \in \mathcal{T}}$ show the matrix of load scheduling for each flexible appliance during a day.

Moreover, the function $\mathcal{H}_k \triangleq [i_k, j_k]$ shows the feasible working hours of each flexible appliance $k \in \mathcal{N}_f$, where the variables i_k and j_k denote the initial and eventual time durations required for accomplishing the task of a k household, and the variable $\mathcal{H}_k$ shows the total parked time of an EV in the house. Thus, we get the following problem for $a_{k,t}$ using equation 1:

$$\begin{cases} P_{k,low} \le a_{k,t} \le P_{k,high} & \forall t \in \mathcal{H}_k \\ a_{k,t} = 0, & otherwise \end{cases} \qquad (1)$$

where, $P_{k,low}$ and $P_{k,high}$ show the lowest and highest consumed electricity by an appliance k during time t, and measured considering its rated power consumption [25]. In addition, a different *time-coupled* problem for $l_{k,t}$ associated with the total power commutation of a household during the working time $\mathcal{H}_k$ is computed by the formulation given in equation 2.

$$\sum_{t=i_k}^{j_k} l_{k,t} \ge l_{k,low} \qquad (2)$$

where, $l_{k,low}$ is the lowest power, consumed by an appliance k to accomplish the assigned task. For instance, $l_{k,ow}$ is supposed to be 16kWh for driving an EV to 40-mile distance [26]. This problem assures that the assigned task will be accomplished till the given deadline j_k. In general, the total demand of a power network during time $\mathcal{T}$ could be computed through equation 3.

$$L_t = L_{nf,t} + L_{f,t} = L_{nf,t} + \sum_{k \in \mathcal{N}_f} l_{k,t} \qquad (3)$$

where, $L_{nf,t}$ is a constant.

B. Voltage Regulator (VR) Modelling

To show the transmission model of the power grid, and to define different entities of a distribution system, a single line grid model comprising multiple buses have been used [7,24]. Let $B = \{b_0, b_1, \dots, b_n\}$ show the collection of network buses. A power transformer is connected to the bus b_0 it directly acquires power from the utility grid, and then distributes it to the consumers (or sell it back to the grid). A set of households $\mathcal{N}_k$ is connected to each bus $b_k \in B \setminus \{b_0\}$. Hence, we get $\bigcup_{k=1}^{B} \mathcal{N}_k = \mathcal{N}$.

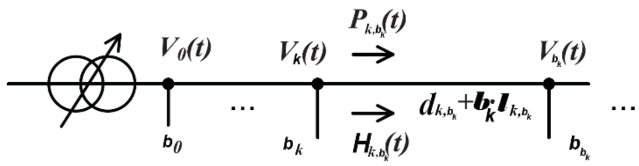

Fig 1: Power flow between two adjacently connected network buses.

The shown power transformer in Fig 1, is a distribution transformer, which step downs the voltages injected by the main transmission lines (over 133 kV) to a distribution level (at 11 kV), here b_0 denotes the distribution side of this power transformer.

It can be noticed that DGs are connected to the multiple buses, referred as *generation buses'* and other buses are referred as load *feeding buses.* $D\mathcal{R}_k$ has been used to show the set of multiple DGs connected with bus b_1, hence, $\bigcup_{k=1}^{B} D\mathcal{R}_k = \mathcal{R}$.

By determining the line impedance value, the value of voltages on each bus can be computed by using the power flow analysis method to calculate the active and reactive power flow [7,27]. Fig 1 shows the relationship between voltage levels of two adjacently located network buses during time t, e.g., $V_{b1}(t)$ and $V_{b2}(t)$ and computed by equation 4 [28].

$$V_{b1}(t) - V_{b2}(t) = \frac{P_{k,b2}(t) \cdot d_{k,b2} + Q_{k,b2} \cdot w_{ks}}{V_{b2}(t)} \qquad (4)$$

where, $P_{k,b1}(t)$ and $Q_{k,b2}$ denotes the active power and reactive power supplied by the bus$_{b1}$ and bus$_{b2}$ for the time t, respectively, in addition the formulation, $d_{k,b2} + b \cdot Z_{b,k}$ represent the impedance of main feeder $k - b$. Equation 4 can be redefined in per unit approximation as given in equation 5.

$$V_k(t) - V_x(t) = P_{k,b1}(t) \cdot d_{k,b2} + Q_{k,1}(t) \cdot w_{k,s} \qquad (5)$$

where the variables $P_k(t)$ and $Q_k(t)$ show the active power and reactive power of bus b_1 for the time t, $V_k(t)$ is the total voltage of an appliance, and $V_x(t)$ are the voltages at VR tap respectively, thus we get equation 6.

$$\begin{cases} P_{k-1,k(}(t) = -\sum_{b2=k+1}^{M} P_{b2}(t) - P_k(t) = -\sum_{s=k}^{M} P_{b1}(t) \\ Q_{k-1,k(}(t) = -\sum_{b2=k+1}^{M} Q_{b2}(t) - Q_{b1}(t) = -\sum_{s=k}^{M} Q_{b2}(t) \end{cases} \qquad (6)$$

It has been inferred that $L_{k,b_k} = \sum_{b \in \mathcal{N}_{k,}} l_{k,b_k}$ is the total load on a bus b_k during time t. Because the total load of household is fully fed by the active power, it can be computed by following formulation given in equation 7.

$$P_k(t) = DR_{k,t} - L_{kt} \qquad (7)$$

where, $L_{k,t} = \sum_{b_k \in \mathcal{O}\mathcal{N}_k} e_{r,t}$ show the supplied power by DGs at bus b_k (e.g., $DR_{k,t} > L_{kt}$), and $P_k(t)$ is a positive variable shows the distributed power by the bus b_k, and it also show the decrease in voltage levels at bus b_0. By using equation 5, the relationship has been formulated between the increasing and decreasing voltage levels i.e., $b_k(1 \le k \le B)$ and b_0, computed by equation 8.

$$V_k(t) = V_0(t) - \sum_{s=1}^{k} \big(P_{b_{k-1},b_k}(t) d_{b_{k-1},b_k} + Y_{b_{k-1},b_k}(t) w_{b_{k-1},b_k}\big) \quad (8)$$

Voltage stabilization is compulsory for each bus. Let, V_{low} and V_{high} are the minimum and maximum voltages on a bus, and V^* show the nominal range of voltages on other distribution end of the gird. It could be narrated as $V_{low} = 0.9 \cdot V^*$, while the range of rated voltages, $V_{high} = 1.1 \cdot V^*$. Hence, by using equation 6 and 8, the voltage regulation problem for bus B_k during time t is defined as given in equation 9.

$$V_{low} < V_0(t) + \sum_{b_k=1}^{k} \left\{ \sum_{c_t-s}^{B} \big(DR_{low,t} - L_{c_t}\big) \cdot d_{b_{k-1},b_k} + \sum_{c=s}^{M} Q_{low}(t) \cdot w_{b_{k-1},b_k} \right\} < V_{high} \quad (9)$$

As stated above, d_{b_{k-1},b_k} and w_{b_{k-1},b_k} are constants, while $\sum_{low=b_k}^{B} Q_{low}(t)$ show the reactive power supplied by bus $B_{b_k}$to bus b_{b_k+1}, which can also be calculated separately for each bus. In addition, the $DR_{k,t}$ shows the electricity generated by renewable at bus $b_{\mathcal{r}}$ which is computed by the proposed generation model. While, equation 9 is defined to overcome the problems faced by the aggregator during load stabilization for each bus.

In order to stabilize the decentralized power network, the overall power generation capacity of renewables should not exceed from the transformer rating. Let, P_{high} should be equal to the rated power that could be supplied by a transformer, in this scenario, the maximum capacity of this system in distributed network can be interpreted by $\sum_{k=1}^{B}\big(L_{k,t} - DR_{k,t}\big) \le P_{high}$. As given in equation 6 and 7, it is a reciprocal of equation 10.

$$\sum_{k \in \mathcal{N}_f} l_{k,t} \le \psi_t \quad (10)$$

where, $\psi_t = P_{high} + \sum_{r=1}^{R} e_{r,t}$.

In addition, the connected VRs can be used to change voltage levels of first bus by taps changing according to the power demand [28]. It is inferred that it is a collection of VR taps $\mathcal{X}$ for load leveling, (i.e., $|\mathcal{X}| = 34$ for 34 step LTCs). Each individual tap shows the resultant voltage $\mathcal{v} \in \mathcal{V}$ on bus b_0: $V_{0,x} \triangleq \Gamma(x)$, here, $\Gamma(\cdot)$ is a linear function. The variable $x_t \in \mathcal{X}$ shows the changes in VR taps position during time t, hence equation 9 can also be redefine as equation 11.

$$V_{low} < \Gamma(x_t) + \sum_{s=1}^{k} \left\{ \sum_{c-s}^{M} \big(DR_{low,t} - L_{low,t}\big) \cdot d_{b_{k-1},b_k} + \sum_{c=s}^{M} Q_{low}(t) \cdot w_{b_{k-1},b_k} \right\} < V_{high} \quad (11)$$

C. Electricity Generation Cost Modelling

Let both consumers and power distributers are placed in a set. If the produced electricity by DGs is enough to even out consumers load during time t, e.g., $L_t \le E_t$, then it is assumed that this set is capable to self-sustain over the following time period. When consumer's load increases from the DGs power generation, then this set must purchase electricity from the national grid i.e., $L_t \le E_t$ The selling price of electricity is inferred to be same as purchasing cost. Hence, for this set, the electricity cost on main grid side, is the only concerned cost, which emphasizes load scheduling, but it deviates during different time slots, however, it could be anticipated by the day-ahead load demand forecasting method, i.e., the per hour energy pricing method of Ontario Power Company, Canada. In order to represent the electricity price, we let c_t during time t, the total cost of electricity C_e can be computed by equation 12.

$$C_e = \sum_{t \in \mathcal{T}} \big(c_t \cdot (L_t - E_t)\big), \quad (12)$$

Now, if $(L_t - E_t)$, C_e value is negative, then it shows the utility company can generate profit by selling energy to the national grid: if not, C_e is the total electricity purchased by the utility company from the national grid to flatten the consumers load.

IV. Mathematical Model Formulation

For voltage stabilization as well as for electricity generation cost minimization, a separate mathematical model is proposed in this research. This section covers the mathematical formulation of the joint voltage stabilization and load scheduling problem as MIINLP constraint. Since the MIINLP constraint is extremely complex to solve, therefore, this constraint is solved as a dual constraint, by further decomposing it into two sub-constraints which are easy to compute.

A. Problem Intilization

Total cost of the generated electricity C_e is the initial cost, determined by analyzing the total power supplied by the renewables, which differs during different time slots $t \in \mathcal{T}$. In addition, continuous tap changing of VRs have shortens its working life due to mechanical wear/tear. Therefore, repairing or replacing cost of VRs have also been included, by comparing the differences between new and previous VR tap settings [7,28]. This relative cost function is initialized as $\Delta(\cdot) : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$, e.g., the wear/tear cost of VRs over the time period $t \in \mathcal{T}$ is evaluated by $\Delta(x_t, x_{t-1})$, here $\Delta(x_t, x_{t-1}) = 0$, if $x_t = x_{t-1}$: if not, $\Delta(x_t, x_{t-1}) = c_l$. In addition, let $\Delta(x_1, x_0) = 0$ is pre-set value and the function $\boldsymbol{x} \triangleq [x_t]_{t \in \mathcal{T}}$ is defined to show the position of tap changer vector for VRs during 24 hours, then the total cost of managing VR is $C_{fr} = \sum_{t \in \mathcal{T}} \Delta(x_t, x_{t-1})$. Note that, the total cost for managing VR taps $C_{f,r}$ is independently included in total electricity cost C_e, thus the overall cost can be determined by equation 13.

$$C_e(x, \boldsymbol{Y}) = \sum_{t \in \mathcal{T}} \{C_t \cdot \big(L_{u,t} + \sum_{t \in \mathcal{N}_v} l_{k,t} - E_{r,t} + \Delta(x_t, x_{t-1})\big)\} \quad (13)$$

The joint voltage regulation and load scheduling constraint could be established by the following expressions as $\boldsymbol{x} = \{x_1, \ldots, x_T\}$ and $\boldsymbol{Y} = \{l_{k,t} | \forall k \in \mathcal{N}_f \forall t \in \mathcal{T}\}$ to **(PP)** $\min C(\boldsymbol{x}, \boldsymbol{Y})$

Apparently, **(PP)** is the MIINLP constraint, because, it is a non-convex objective function (i.e., $\sum_{t \in \mathcal{T}} \Delta(x_t, x_{t-1})$, and only provide conventional solution [29] which could not be implemented for controlling the load scheduling constraints. After precise analysis, it has been determined, in equation (11) $\boldsymbol{x}$ and $\boldsymbol{Y}$ are the only corresponding variables used to optimize **(PP)**. Therefore, the Lagrangian relaxation technique is used to solve this constraint by separating it into two independent optimization constraints for $\boldsymbol{Y}$ and $\boldsymbol{x}$ constraints.

B. Separation of the Constraint

In the proposed model, constraint (11) is the only problem which has been used to compile the optimization of sub-constraints $\boldsymbol{Y}$ and $\boldsymbol{x}$, therefore in order to further enhance the computational capability of this constraint, I have applied the Lagrange multiplier matrixes as:

$$\lambda = \{\lambda_{b,t} > 0 | 1 \leq b \leq B, 1 \leq t \leq T\}$$

while $s = \{s_{b,t} > 0 | 1 \leq b \leq B, 1 \leq t \leq T\}$

Thus, the Lagrangian $L(\cdot)$ is lined to the initial constraint (PP) as shown in equation 14,

$$\mathcal{L}(x, A, \lambda, s) = \sum_{t\in\mathcal{T}}\{c(t)\sum_{k\in\mathcal{N}_v} l_{k,t} + \Delta(x_t, x_{t-1}) + b_t\}$$

$$+\sum_{b=1}^{B}\sum_{t=1}^{T}\lambda_{b,t}\left(\Gamma(x_t) - \sum_{p=b}^{B}\sum_{y=p}^{B}\sum_{k\in B_y}(d_{p-1,p}l_{k,t}) + v_b - V_{high}\right)$$

$$+\sum_{b=1}^{B}\sum_{t=1}^{T}s_{b,t}\left(V_{low}\Gamma(l_t) + \sum_{p=b}^{B}\sum_{y=p}^{B}\sum_{k\in B_y}(d_{p-1,p}l_{k,t}) - v_{b,t}\right) \quad (14)$$

where, $v_{b,t} = \sum_{p=b}^{B}\sum_{y=p}^{B}(d_{p-1,p}e_{y,t} + x_{p-1,p}Z_{y,t})$

and

$b_t = c(t) \cdot (L_u(t) - E(t))$.

It can be seen that both these constraints are constants, and showing the functions of $\alpha_t \triangleq [\alpha_{1,t}, \ldots, \alpha_{|\mathcal{N}_v|}, t]^T$ and $l_t = [l_{k,t}, \ldots, l_{|\mathcal{N}_f|}, t]^T$ and define as equations 15 and 16.

$$(\alpha_t)^T l_t \triangleq \sum_{b=1}^{B}\left[(\lambda_{b,t} - x_{b,t})\sum_{p=b}^{B}\sum_{y=p}^{B}\sum_{k\in B}(d_{p-1,p}d_{k,t})\right]$$

$$\beta_t \triangleq \sum_{b=1}^{B}(\lambda_{b,t} - x_{b,t}) \quad (15)$$

$$\theta = \sum_{b=1}^{B}\sum_{t=1}^{T}\left[\lambda_{b,t}(v_{b,t} - V_{high}) + x_{b,t}(V_{low} - v_{b,t})\right] + \sum_{t=1}^{T} b_t. \quad (16)$$

Hence, the Lagrangian formulation can be defined as equation 17.

$$\mathcal{L}(x, A, \lambda, s) = \sum_{t\in\mathcal{T}}\left(\sum_{k\in\mathcal{N}_v} c(t)l_{k,t} - (a)^T l_t\right)$$

$$+\sum_{t\in\mathcal{T}}[\Delta(x_t, x_{t-1}) + \beta_t \cdot \Gamma(x_t)] \quad (13)$$

In addition, the joint formulation is defined as equation 18:

$$\mathcal{H}(\lambda, s) = \operatorname*{Inf}_{x,A} \mathcal{L}(x, A, \lambda, s) \quad (14)$$

In order to separate x and $\boldsymbol{Y}$ from this joint constraint, we define the following sub-constraints shown in equation 19 and 20.

$$(\textbf{SC1})\ \ \mathcal{S}_1(\lambda, \mathfrak{x}) \triangleq \min_A \sum_{t\in\mathcal{T}}\left(\sum_{k\in\mathcal{N}_v} c_t l_{kt} - (a_t)^T l_t\right) \quad (19)$$

s.t, E.q, (1, 2 and 10)

$$(\textbf{SC2})\ \ \mathcal{S}_2(\lambda, s) \triangleq \min_{q} \sum_{t\in\mathcal{T}}[\Delta(x_t, x_{t-1}) + B_t \cdot \Gamma(x_t)] \quad (20)$$

s.t, $x_t \in [1, |\mathcal{X}|] \cap \mathbb{Z}\ \forall t \in \mathcal{T}$

where, θ is an independent variable in x, Y constraints thus, for decoupling, the joint formulation can be redefined as equation 21.

$$\mathcal{F}(\lambda, \mathfrak{x}) = \mathcal{S}_1(\lambda, s) + \mathcal{S}_2(\lambda, s) + \theta \quad (21)$$

Let, initial **(PP)** constraint is separated into two sub-constraints: **(SC1)** for load scheduling of the flexible households, and **(SC2)** is used to assess the VR taps positions.

Eventually, this joint constraint is used to enhance the joint formulation of λ and s, i.e., shown in equation 22 and 23.

$$(\textbf{DP})\quad \min_{\lambda,\mathfrak{x}} \mathcal{H}(\lambda, \mathfrak{x}) \quad (22)$$

$$\text{s.t.}\quad \lambda_{b,t} \geq 0, s_{b,t} \geq 0 \forall b \in B, t \in \mathcal{T}. \quad (23)$$

where, the l_t is the discrete variable, therefore, the non-convex formulation $\sum_{t\in\mathcal{T}}\Delta(x_t, x_{t-1})$ in **(PP)**, is a weak duality function and could only be assured by the Lagrangian function where the duality space is continuous [29]. We infer $\mathcal{H}$ and $\mathcal{P}$ will be the achieved by **(DP)** and **(PP)**. As a result, we get, $\mathcal{H} < P$, this condition sustains for each forecasted solution, hence, $\mathcal{H}$ is shifted towards the lowest bound of $\mathcal{P}$ [30].

V. Solution of The Joint Constraint and Sub-Constraints

This section covers the solution of initial constraint by computing the joint constraint and two sub-constraints.

A. Sub-gradient Model for Joint Constraint.

If **(SC1)** and **(SC2)** could be efficiently computed by λ and $\mathfrak{x}$, then the "dual problem (DP) is considered as a joint constraint" and it could be rationalized in the reverse course which is a fractional gradient of the Lagrangian joint function [30-32], and defined as equation 24.

$$\begin{cases}\lambda_{b,t}(k+1) = [\lambda_{b,t}(k) + \gamma_\lambda \cdot u_{\lambda,b,t}(k)]^+ \\ s_{b,t}(k+1) = [s_{b,t}(k) + \gamma_\lambda \cdot u_{\mathfrak{x},b,t}(k)]^+\end{cases} \quad (24)$$

where , the variable $k \in N^+$ denotes the iteration index, $\gamma_\lambda > 0$ and $\gamma_\mathfrak{x} > 0$ denotes the tap step size adjustments and also show the rate of convergence, the terms $\mu_{\lambda,b,t}(k)$ and $\mu_{\mathfrak{q},b,t}(k)$ are the sub-gradients of the joint function defined according to the values of $\lambda_{b,t}$ and $\mathfrak{x}_{b,t}$, respectively as shown in equation 25.

$$\begin{cases}\mu_{\lambda,b,t}(c) = \dfrac{\partial\mathcal{H}(\lambda,\mathfrak{x})}{\partial\lambda} = v_{b,t} + \Gamma(x_t(k)) - V_{high} \\ \quad -\sum_{p=b}^{B}\sum_{y=p}^{B}\sum_{k\in B_y}\left(d_{p-1,p}, l_{k,t}(k)\right) \\ \mu_{\mathfrak{q},l,t}(k) = \dfrac{\partial\mathcal{H}(\lambda,\mathfrak{x})}{\partial\lambda} = V_l - v_{b,t} + \Gamma(x_t(k)) \\ \quad -\sum_{p=b}^{B}\sum_{y=p}^{B}\sum_{k\in B_y}\left(d_{p-1,p}, l_{k,t}(k)\right)\end{cases} \quad (25)$$

where, $v_{b,t} = \sum_{p=b}^{B}\sum_{y=p}^{B}(d_{p-1,p}, e_{z,t} + \mathcal{w}_{p-1,p}Z_{y,t})$, the results for $l_{k,t}(k)$ and $x_t(k)$ could be achieved by computing **(SC1)** and **(SC2).** Hence, the indentation of **(DP)** constantly sustains and the Lagrangian accumulators could be obtained by computing the above given sub-gradient problem.

B. Solution of the Sub-constraints

These subsequent paragraphs cover the solution of the above given sub-constraints **(SC1)** and **(SC2)**. As the iteration process is used to solve the joint constraint; therefore, the sub-constraints must be addressed effectively to assure the reliability and efficiency of the proposed model. The load scheduling constraint, i.e., **(SCI),** has been defined as the linear optimization constraint, which could be solved directly through conventional linear programming methods [33,34], and the VRs adjusting constraint, e.g., **(SC2)** is the integral optimization constraint, which is complex to solve directly. Therefore, we are mainly focusing on finding the polynomial solution for **(SC2)** as follows:

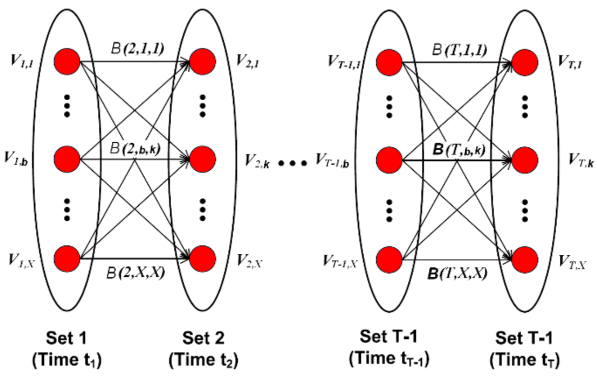

Fig 2: The proposed graph pattern which is derived to evaluate **(SC2)**.

1) Solution of (SC1): The s *and* λ are the functions of *Lagrange multiplier matrix*, and α_t, can be set as constants for the each time slot $t \in \mathcal{T}$. Consider, if $\varphi_{k,t} \triangleq c_t - \alpha_{k,t}$ is fixed then the objective function from **(SC1)** can been redefined as equation 26.

$$P_1(\lambda, s) = \max_{Y} \sum_{t\in\mathcal{T}} \sum_{k\in\mathcal{N}} (\varphi_{k,t} \cdot l_{k.t}) \tag{26}$$

Algorithm 1: 'Bellman Ford' based optimization for (SC2)

Inputs: $\beta \quad = \{\beta_1, \dots, \beta_T\}$ and the graph R;
Outputs: The 'tap position vector' $x = [x_1, \dots, x_T]$ and the 'optimal value' of $S_2(\lambda, s)$;
Initialization of 'vertex matrix' $n[T-1][X]$, source node H, edge matrix $b[T][X][X]$ in accordance with equation 29 and 30.

$[src \leftarrow H]$, dist $[H] \leftarrow 0$;

for each 'vertex' $n[t][b_k]$ **in** the 'vertex matrix' **do**;

$dist[t][b_k] \leftarrow \boldsymbol{infinity}$;

precursor$[t][b_k] \leftarrow \boldsymbol{null}$;

end;

for each 'vertex' $n[t][b_k]$ **in** the 'vertex matrix' **do**;

for each 'edge' $m[t+1][b_k][k]$ in the 'edge matrix' **do**;

if $dist[t+1][k] + b[t+1][b_k][k] < dist[t][b_k]$ **then**;

$dist[t][b_k] \leftarrow dist[t+1][k] + m[t+1][b_k][k]$;

$precursor[t][b_k] \leftarrow n[t+1][k]$;**end**

end

end

$S_2(\boldsymbol{\lambda}, \boldsymbol{x}) \leftarrow \max_{1\le s\le X} dist[1][b_k]$;

$f \leftarrow arg \max_{1\le s\le X} dist[1][b_k]$;

for each (t) from $(1\ to\ T)$ **do**;

if $(t = T)$

then

Set $\mathfrak{x}_t$ in accordance with (20);

else;

$s_t \leftarrow f$;

$f \leftarrow precursor(f)$;

end

end

return $S_2(\lambda, s)$ and s;

and this constraint has been redefined as equation 27.

$$\begin{cases} \gamma_k^{min} \le l_{k,t} \le \gamma_k^{max} \forall k \in \mathcal{N}_v \forall \in \mathcal{T} \\ \sum_{t\in\mathcal{T}} l_{k,t} \ge P_{k,on} \\ \sum_{k\in\mathcal{N}_f} l_{k,t} \le \psi \quad \forall \in \mathcal{T} \end{cases} \tag{27}$$

where, $\gamma_k^{min} = \gamma_k^{max} = 0 \ \forall t \notin [i_k, j_k]$. Hence, **(SC1)** turned into a classical linear programming constraint, the scheduling algorithm proposed in [14] is a feasible solution for solving this constraint effectively uses load forecasting technique in order to implement the linear programming and assures the polynomial collaboration.

2) Solution of (SC2): The s *and* λ are *Lagrange multiplier matrix* functions and, $\beta_t(\beta_t \in \mathbb{R})$ can be set as constant for the each time slot $t \in \mathcal{T}$. It has to be noted that the objective function for the constraint **(SC2)** determines each alteration of x_t and x_{t-1}, hence, the achieved solution can be declared as globally optimal. Furhter, I have also aggravated this solution in such manner: it will only follow the defiend path in the directed graph.

Fig 2 shows the defined directed graph R comprises time slots T, and also show the autonomous vertex sets, in which each set $t(1 \le t \le T)$, consists of X number of nodes. In order to signify $s(1 \le s \le X)$ in a time slot set (t), n_{t,b_k} are used in this work. As long as $(2 \le t \le T)$ is concerned, each node s of a set $(t-1)$ comprises an edge corresponding to each hourly slot set (t). The mass of this edge on a node s prevails in a set $(t-1)$ to a node b_k for k set of households which is $b(t, b_k, c)$.

Now, we are focusing on the objective function, deals with the **(SC2).** Consider we characterize $U(t-1,t) \triangleq (x_t, x_{t-1}) + \beta_t \cdot \Gamma(x_t)$ for each $(1 \le t \le T)$, thus the objective function could be refined as $S_2(\lambda, s) = \sum_{t=1}^{T} U(t-1,t)$. The main focus here is to evaluate the optimal positions of x_t for the set of VR tapings $\mathcal{X}$ for each time slot t to achieve $S_2(\lambda, s)$.

Algorithm 2: For Day-ahead Demand Scheduling.

Inputs: Mandatory load vector k, anticipated electricity generation vector E, set load vector L_μ and the cost vector k;

Outputs: The optimal load scheduling profile $\boldsymbol{Y}(k)$ and the adjusted positions vector of VR taps $x(k)$;

Let $k = 0$; Initialize Legranigen multipliers $\lambda_{b,t}(k)$ and $s_{b,t}(k)$;

repeat

With $\lambda_{b,t}(k)$ and $s_{b,t}(k)$, compute the 'scheduled load' matrix $\boldsymbol{Y}(k)$ by computing **(SC1)**, and asses the 'tap position' vector $\boldsymbol{x}(k)$, while computing **(SP2)** in accordance to the '**Algorithm 1**';

With $l_{k,t}(k)$ and $x_t(k)$, upgrade $\lambda_{b,t}(k+1)$ and $s_{b,t}(k+1)$ in accordance with equations 23 and 24;

until (i) *k overlaps the highest iteration numbers; or (ii) the space between $\mathcal{Q}$ and $\mathcal{P}$ at minimum level;*

return $\boldsymbol{Y}(k)$ and $\boldsymbol{x}(k)$;

In case we fix each time slot t, and the position of VR taps $b_k \in \mathcal{X}$ within a node at n_{t,b_k} in a time set (t) of R, then the mass $b(t, b_k, c)(1 \leq b_k \leq X, 1 \leq k \leq X)$ could be redefined as equation 28.

$$\begin{cases} b(2, b_k, k) = \Delta(b_k, k) + \beta_1\Gamma(b_k) + \beta_2\Gamma(k), if\ t = 2 \\ b(t, b_k, k) = \Delta(b_k, k) + \beta_1\Gamma(k), if\ 2 < t \leq T \end{cases} \quad (15)$$

Algorithm 3: The Intraday Load Stabilization

Inputs; Similar to 'Algorithm 2';

Outputs: The stabilized load matrix Y^* and the 'tap position vector' $\boldsymbol{x}^*$ over the time slot '2 to T';

For primal time slot adjust LTC tap position and 'schedule load' by using the result acquired from Algorithm 2;

Add $\boldsymbol{l}_1$ as the initial column of $\boldsymbol{Y}^*$, $\boldsymbol{x_t}$ and as the primal element for $\boldsymbol{x}^*$;

repeat

In start of the time $t(2 \leq t \leq T)$,
update the projected power generation vector $\boldsymbol{E}' = \{E_t', \ldots, E_T'\}$, anticipated load vector k' together with scheduling load of the previous $T - t$ time slot;

By updating E' and k', run Algorithm 2 to achieve the real time schedule for stabilizing load l_t' and 'tap position' vector x_t over the time t;

Add l_t as t^{th} column of $\boldsymbol{Y}^*$, x_t as t^{th} element of the x^*;

until $t = T$;

return $\boldsymbol{Y}^*$ and $\boldsymbol{x}^*$

Thus, **(SC2)** has been equally transformed to select a node $n_{t,b}$ for each set (t) of R, to reduce the overall mass of the entire path. Those nodes selected to create a fixed conjunction path are referred as path nodes.

To solve this constraint, some more alterations for the above graph are proposed. If each path node, the set 1 to set $(t-1)$ has been assessed in such a manner that it can leniently select the appropriate connection of a node from set (t). It shows, if a path node has been pre-established for a time set $(t-1)$, then the optimal preference of a set (t) supposed to be at node' b_k which has the lowest mass $min_{1 \leq c \leq X}\left(\Delta(s, c) + \beta_t\Gamma(k)\right)$, Hence, it can be observed that time set (t) in the form of solitary node $\mathcal{S}$, in addition, the mass of this edge is relative to the node b for a time set $(t-1)$ and computed by equation 29.

$$b(T, b_k, \mathcal{S}) = \min_{1 \leq k \leq X} b(t, b_k, k) \quad (29)$$

while the path node of a set (t) can be defined as equation 30.

$$\mathcal{S} = \arg \min_{1 \leq b_k \leq X} b(t, b_k, k) \quad (30)$$

If $\mathcal{S}$ is selected as a "*Source Node*", while the '*Path Node'* n_{1,b_k} from primal set is selected as destination node, then it overturns each edge direction located in the graph R, thus the entire path from $\mathcal{S}$ to n_{1,b_k} exhibits lowest mass. So, we can consistently compute the value of the closest path from $\mathcal{S}$ to $n_{1,b_k}(1 \leq b_k \leq X)$, and it could also be declared as the optimal solution of **(SC2)**. .It must be noted that the mass of each 'edge' in $\mathcal{H}$ might be negative, in this case, the closest path of a node can be computed by using the Bellman Ford method. The main approach of the proposed solution for **(SP2)** is $B(X^3T^2)$.

VI. The Consumer-Grid Interaction and Laod Schedlung Scheme

The section explains the complete working procedure of the proposed model and defines the consumer-grid interaction-based load scheduling technique to reduce the overall power consumption cost, to eliminate surges and to counter voltage fluctuations disturbing the generation system. The proposed load scheduling model is based on two processes; first day-ahead (DA) scheduling, in which a central management office forecasts load schedules and tap position vectors for LTC's for the next 24 hourly slots, while the second process is based on the methodology in which the consumer load is directly controlled by the central aggregator office for all 24 hours, in this method the central management center is responsible to manage the real time load and the positions of VR taps for each time slot.

A. DA Load Forecasting

Preliminarily, initially proposed constraint defined to eliminate the voltage fluctuations introduced by renewables is considered , which is the main purpose of consumer-grid synchronized load scheduling policy. In the proposed algorithms, excluding decision making variables x and $\boldsymbol{Y}$, each other parameter of primal constraint is determined in advance, or it is anticipated one day ahead. Along electricity cost of the central power grid $c = \{c_t | \forall t \in \mathcal{T}\}$ and the required power for flexible households $k = \{k_t | \forall t \in \mathcal{N}_f\}$ is also pre-determined. In addition, the total power required to power fixed households $L_{nf} = \{L_{nf,t} | t \in \mathcal{T}\}$, as well as the feasible statistics of the renewable power generation $E = \{E_t | \forall t \in \mathcal{T}\}$ are also anticipated in advance. Hence, the Algorithm 2 illustrates the objective approach of the day ahead scheduling and proceeds the optimal load scheduling on a global scale for flexible households and the positions of LTC taps for the next 24-hourly slots.

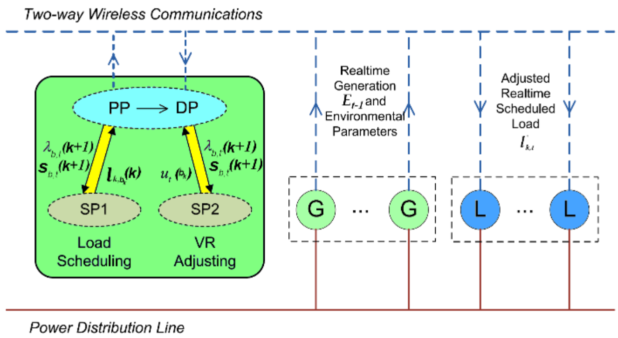

Fig 3: The proposed intra-day load stabilizing strategy.

B. Intra-day Load Stabalizing

Algorithm 2 illustrates the offline load stabilizing method, which executes one day-ahead to forecast the next day renewable production. However, in literature, several proposed renewable generation forecasting algorithms can precisely predict the feasible renewables generation, but the error in power prediction statistics anticipation is still not fully eliminated, which can affect the projection accuracy. In quest to further reduce the impact of power generation forecasting error, an intra-day load stabilizing and scheduling algorithm is proposed to upgrade the load scheduling in real time l_t for the flexible appliances and to determine the appropriate position of LTC taps x_t during each time slot $t(2 \leq t \leq T)$ for the next day.

This load scheduling algorithm effectively determines the next day load and renewable generation statistics, because it is using day-ahead forecasted load schedules, as presented in Fig 3, prior to the execution of first time slot, "*Algorithm 2*" is presented to evaluate the required energy demand to power load L, along it also determines the position vector x of LTC taps, for next time slot $\mathcal{T}$. Meanwhile, before the execution of t'th $(2 \leq t \leq T)$ time slot, the central control office again computes the power production vector $E' = \{E'_t, \ldots, E'_T\}$, considering the power generation statistics of previous time slot $T-1$. Moreover, the effect of real time ecological conditions (i.e., wind speed, and photovoltaic radiation) are also determined. After that, E' is used as an input in order to execute the Algorithm 2 for anticipating real time load scheduling vector L_t and appropriate tap positions x_t.

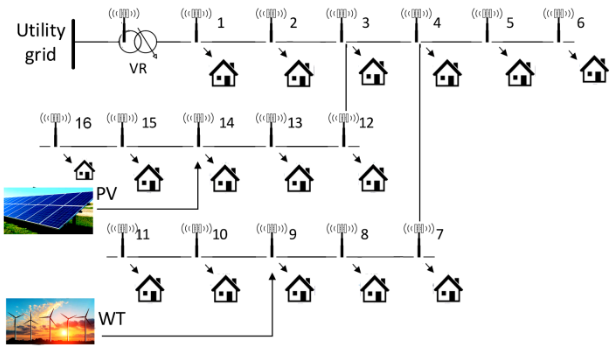

Fig 4: Illustration of the Proposed Model for Simulation

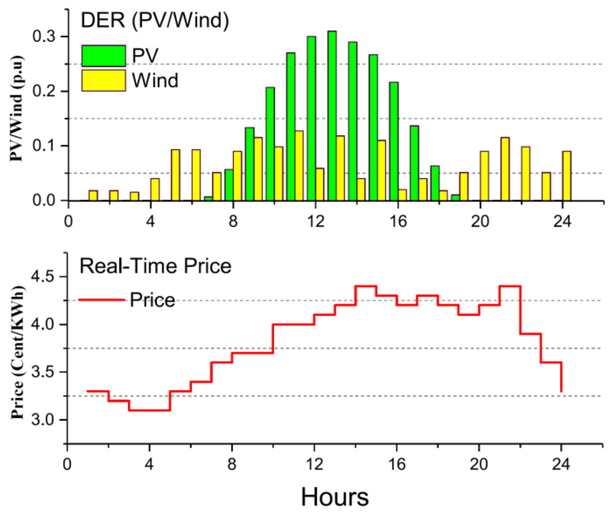

Fig 5: Generated electricity pattern by renewables and production cost.

VII. Case Studies

In this section, the performance of the proposed algorithm is evaluated during load scheduling tasks and power generation forecasting, actual renewable generation and load demand statistics are penetrated. The simulations have been carried out on 16-bus grid network proposed in [16]. For better load management a VR is added between bus 1 and main power grid, i.e., with the bus 0. The photovoltaic power plants are connected to the bus 14, while bus 15 is connected to the windmill and as presented in Fig 4.

A. Simulated System Specifications

The simulated VR was manufactured by the McGraw Edison and it is used for voltage regulation of single phase, whose voltage levels can be adjusted by 85% and 116% of the nominal voltages [37]. The statistics of the energy produced by photovoltaic and windmills is acquired from the Belgium's renewable energy department [35,36] and 'UQ' solar [37]. The real time energy cost statistics are acquired from the Ameron Ilionis [38], which vigorously alters its energy prices during each hour.

Fig 5 defines the renewable power production and energy cost statistics. The load profiling data of each consumer during different time slots is acquired by the advance metering infrastructure (AMI) installed by the Northern Walterloo-Hydro, in the premises of Laurel-wood, Waterloo Ontario Canada [7]. The flexible household appliances load accounts about 32% of the overall load of each customer [38], having load scheduling problem for each household (i.e., EVs charging load can be directed and scheduled from 16:00 to 20:00 hours).

However, for simulation testing, acquired statistics have been applied to the proposed algorithm to check its capability of load scheduling of day-ahead offline load scheduling algorithm. Voltage regulators (VRs) are used as well as the proposed intra-day algorithm is penetrated in order to schedule the online load by using VRs. A day has been divided in 24 time slots (e.g., one hour is considered as a mandatory schedule slot each day). The results of the proposed algorithms are compared with the method proposed in [39], which is termed as Deng-ad'al algorithm. The Deng's algorithm only targets the optimal load scheduling without evaluating voltage fluctuation constraints. The data of the flexible and non-flexible loads which is used for simulation is given in Table I. A household appliance which is labeled as type 0 is defined as non-flexible load. The simulations are carried out by using the MATLAB R2017a by employing the Mat-power toolbox.

B. Electricity Cost and Load Scheduling

Fig 6 present the comparison of scheduled consumers load, regulated by penetrating the proposed online load scheduling algorithm with the original consumers' load statistics. It could be analyzed that proposed algorithm has successfully scheduled the consumers load and minimized the peak load by enforcing the higher electricity cost during peak hours. Moreover, the online scheduling algorithm also stabilizes the electricity generated by DGs to provide stable power to the consumers, along it can sell the excessively available energy back to the grid at higher rates.

Fig 7 shows the comparison of total energy consumption cost statistics obtained by implementing the Deng's algorithm and proposed online algorithm. It could be analyzed that proposed online algorithm can effectively minimize the power consumption cost for multiple days. Although, the Deng's algorithm is showing lower energy costs as compare to the proposed algorithm, main reason of this difference is, the Deng's algorithm only focuses to optimal schedule of the consumer load without determining the voltage fluctuation constraints. Conversely, the proposed algorithm considers both, which eventually reduces the overall energy cost as well as stabilizes the load on the main power gird.

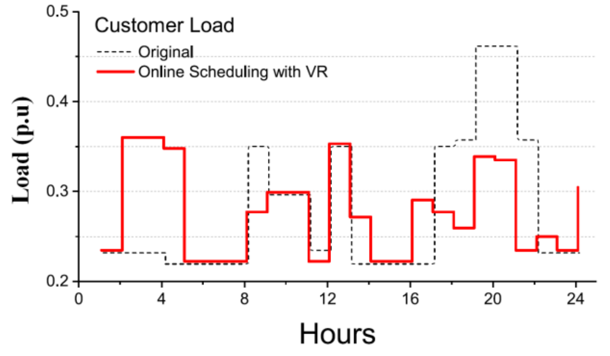

Fig 6: The scheduled load profile of the residential consumers.

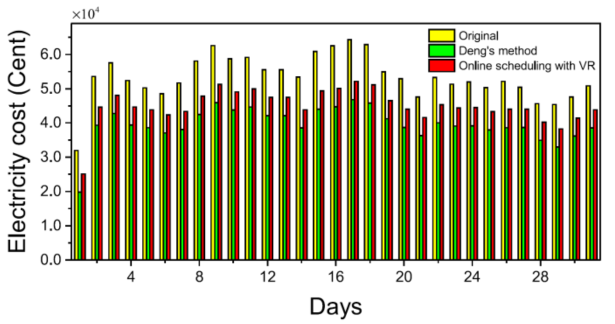

Fig 7: The overall electricity price comparison of different algorithms.

Table I
Household Appliances Using Pattern

Appliances	Required Load' (kW)	Operation Power' (kW)	Starting Time	Load Type	Scheduling Problem'
EVS	15	4.550	18:2	1	18-8:03
Air-conditioner	6	2500	19:15	1	18-21:06
Dishwasher	1.343	0.468	8,13,15	1	12-18:12:
Cloths Dryer	4.112	4.114	11	1	11-22:30
Compressor	2.2	3.1	8	0	-
Room lights	1.00	0.11	17	0	-
Refrigerator	1.33	0.266	0	0	-
Heaters	7.13	0.315	0	0	-

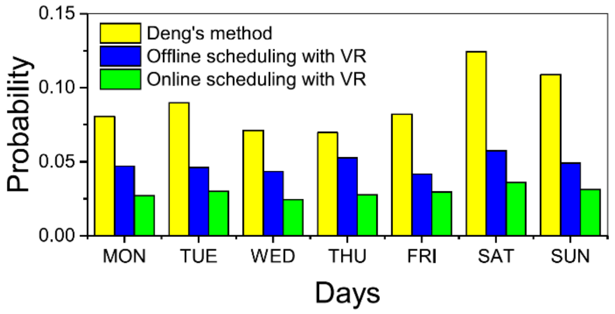

Fig 8: The probability comparisons of the voltage variations.

C. Regulated Voltage Assessment

Fig. 8, shows the comparison of voltage variation difference probabilities of the proposed online load scheduling algorithms with the Deng's algorithm. It is evident from the figure that proposed algorithm has jointly carried out the voltage stabilization and load scheduling, and significantly minimized the voltage fluctuation probabilities of the distribution network as compared to the Deng's algorithm. In addition, online algorithm provides precise pricing details and generated power information as compare to the Deng's method. These voltage variation probabilities can be further minimized by comparing these results to the offline scheduling algorithm.

VIII. CONCLUSION

In this research paper, a joint voltage stabilizing and load scheduling algorithm is proposed for a decentralized power networks to effectively integrate renewable resources. By implementing the power flow analysis technique, a load scheduling problem as a MIINLP constraint is formulated and divided this into two sub-constraints which are completely independent and could be computed separately for achieving optimal solution. In addition, a consumer-grid coordination-based load scheduling scheme has been proposed that comprises online and offline algorithms, to jointly govern the voltage regulation and consumer load scheduling optimization tasks. In last, real life statistics from utility grids are used to conduct simulations analysis to evaluate performance of the proposed algorithms, test results show that the performance of proposed technique is appropriate, and the model could be used for grid stabilization practically. In future, research will focus on distribution network stabilization, where DGs will be equipped with scattered energy storing stations, this system can further contribute to the voltage transients controlling in a gird.

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