Stochastic Optimization of an Active Network Management Scheme for a DER-Rich Distribution Network Comprising Various Aggregators

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Abstract - With large-scale acceptance of solar and wind energy generation into electric grids, large energy storage is expected to provide sufficient flexibility for the safe, stable and economic operation of power systems under uncertainty. Active Network Management (ANM) allows this to happen without having to enlarge the system. This paper presents an ANM-based cost minimization and curtailment model for day-ahead operational planning of active distribution systems. Electric Vehicles (EVs) are managed by EV Aggregators for profit purposes under different parking characteristics in the Vehicle-to-grid mode. A pricing mechanism that defines interaction between the Distribution System Operator (DSO) and EV Aggregators is proposed. Uncertainty terms involve the wind power outputs, solar power outputs and the power demand. The stochastic optimization model created 27 scenarios and solved the minimization problem which involves the grid supply point power, the non-firm power and the aggregator power. This is applied to IEEE-33 bus system and implemented in AIMMS. Results show how the impact of various aggregators' availability profiles help to reduce network operating cost and curtailment of non-firm DGs and improve voltage profiles.

Keywords— Stochastic, ANM, Aggregators, DSO, scenarios

I. Introduction

In recent years, there has been a heightened penetration of distributed energy resources in electricity networks. For example, the global cumulative wind power capacity in 2021 was 845GW [1] while that of solar PV was 942GW [2]. This massive deployment of clean and sustainable renewable energies into power networks is aimed at decarbonization of the economy as well as reduction of network operation costs as fossil fuel prices continue to rise [3].

Control and management of the emerging networks containing high renewable energies is achieved within network constraints utilizing advances in information and communication technologies of active network management schemes. This is a smart alternative to network reinforcement and maximizes hosting capacity [4]. In addition, the impact of electric vehicle (EV) fleet penetration in present-day distribution system is significant due to intermittency of generation. Distribution system operators (DSOs) deploy the aggregated energy storage capability of EV batteries to provide ancillary services (e.g., power grid regulation, spinning reserve, peak load shaving, load leveling and reactive power compensation) in electric grids through controlled charging and discharging in a Vehicle-to-Grid (V2G) mode [5],[6]. In the past, a major source of uncertainty in power system is inability to predict the outage of a system component [7]. As power systems evolve, there are uncertainties associated with integration of weather-dependent pattern of solar and wind energy sources, power consumption pattern of consumers (e.g. electric vehicles) and load growth and electricity price based on forces of demand and supply of electricity [8].

A widespread concept in managing and controlling loads and energy storage and increasing renewable generation in active distribution networks with or without uncertainty in a secure and cost-effective way without necessarily upgrading the network infrastructure and within specified limits is the Active Network Management (ANM) [9],[10].

Previous works have addressed different aspects of optimization of ANM schemes. In [11], a deterministic dynamic OPF that classified available renewable DGs into firm and non-firm was formulated for the ANM scheme with the aim of maximizing the utilization of non-firm DGs (that is, curtailment reduction) and minimize cost of energy. [12] incorporated the stochastic nature of wind power, solar photovoltaic (PV) and small hydro generation into a modified IEEE-30 system modeled with appropriate probability density function (PDF) and solved using metaheuristic algorithm rather than classical OPF. [13] formulated 24-hr deterministic and stochastic optimization models with load and renewable curtailment control in both grid-connected and island operations. For the stochastic model, uncertainty in PV output was done for three scenarios. The study did not include EV control charging control and uncertainty in demand.

[14] proposed a particle swarm optimization approach to consider uncertainty associated with PV and wind turbine (WT) output power using appropriate PDF. Rabiee et al in [15] applied information gap decision theory to model wind power generation uncertainty considering voltage stability constraints.

In [16], a scenario-based approach was used to model uncertainties in wind power generation in the presence of EVs to demonstrate its impact on voltage stability. Silva et al in [17] proposed a model that considered uncertainties in demands, renewable generation, and voltage reference at the point of common coupling (PCC). Several uncertainty modeling methods have been adopted in literature. Some of these are information gap decision theory [15], scenario-based modeling [16], adaptive fuzzy logic [18], robust optimization and probabilistic methods.

Effects of uncertainties in decision-making should be properly examined and traditional deterministic approach which evaluates a single specific scenario is insufficient to achieve this aim. In this paper, we intend to design an

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optimized ANM scheme that minimizes DSO cost of operation and energy curtailment by studying characteristics of different aggregators, their charging/discharging control and how they impact the system. We intend to develop scenario-based multi-period stochastic models that incorporate uncertainties in solar and wind generation and power consumption (demand) pattern including penalty costs.

The remainder of this report/paper is organized thus: Section II: describes the ANM scheme and the embedded technologies (curtailment, EV aggregators, interaction among major players in the ANM scheme); Section III: Problem Formulation for stochastic models; Section IV: Implementation; Section V: result discussion and Section VI: Conclusion.

II. ACTIVE NETWORK MANAGEMENT FRAMEWORK

Secure and optimal operation of active distribution systems (ADS) is the responsibility of DSOs. Due to increasing operational complexity of modern ADS, their roles continue to grow from conventional (which include connection and disconnection of distributed energy resources (DERs), management of outages, planning and maintenance of networks) to emerging/future (peak load management, network congestion management, reactive power support to Transmission System Operators (TSOs), participation in electricity market and voltage support) [19]. In addition, DSOs are expected to develop new models and approaches to account for uncertainty associated with certain parameters in the system [20].

The objective of this work is to minimize the day-ahead operational cost and maximize the use of renewable DGs in the system for efficient and stable services. To achieve this, we propose a framework where the DSO takes charge of the day-ahead operational scheduling of its network by managing curtailment of DG, provision of charging and discharging schedule for EV aggregators and estimating the impact of uncertainty in the system. This requires the DSO to actively enter into commercial agreements with a variety of stakeholders whose behaviour are influenced by the electricity market [21].

A. Distributed Generation Curtailment

It is possible that variable generation from renewable sources are oversupplied at certain times thereby leading to imbalance between power supplied and power demanded in the power grid. The amount of renewable energy output that can be absorbed into the system is also limited by thermal line limits or bus voltage limits [11][22]. Consequently, excess generation is curtailed. Curtailment reduction strategies in use include introduction of energy storage devices and flexible/controllable loads and use of grid policies that require utilities to compensate DG owners for curtailed output [22] and network reconfiguration. In the proposed framework, the DSO agrees to compensate non-firm DG owners for any curtailment of day-ahead scheduled generation.

B. EV Aggregators

EVs are expected to increase significantly in the coming years as the campaign for net-zero emission increase. This is expected to constitute high charging load on electrical networks [23]. EVs combine the features of energy storage and flexible loads useful for curtailment management and have the tendency of limiting curtailment payments and minimizing cost of operation on the DSO. The aggregator also acts as interface between the EV owners and the DSO [24].

The proposed framework considers a number of aggregators including owners of parking infrastructure either at office building, public areas or LongStay car parks where vehicles are left for multiple days (e.g., airports, train stations).

With the intention of offering fair rates to aggregators and allowing DSOs perform energy arbitrage, a system is proposed in which day-ahead MW prices are agreed between the DSO and aggregators. In this framework, these are buy price (price of buying power from aggregator) and sell price (price of selling power to aggregator). Buy price is higher than sell price to allow compensation paid to EV owner for degradation costs caused by additional battery cycling during EV discharge.

C. Framework Description

Fig. 1. shows the structure of the proposed price-based energy management framework and illustrates how different actors involved in the system interact.

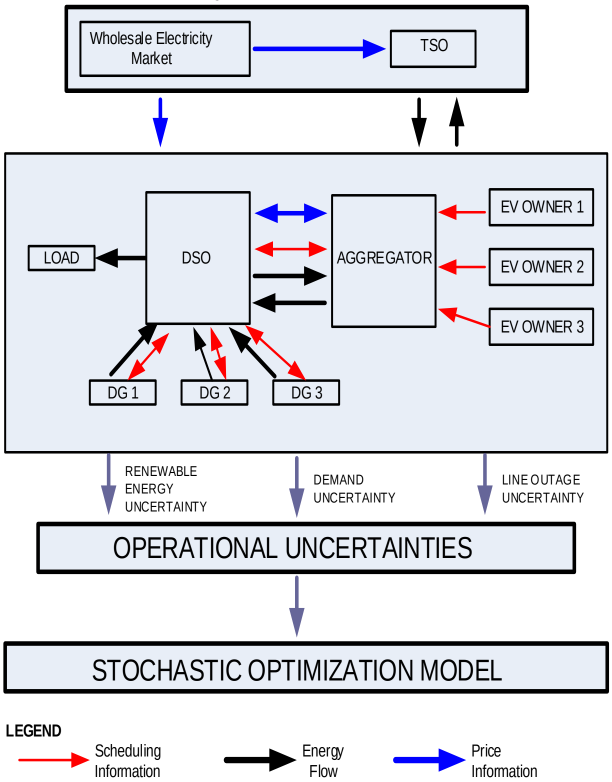

Fig. 1. Structure of the Proposed Energy Management Framework

The day-ahead electricity price is used by the DSO to determine the cost of energy purchase from DG owners and aggregators by arbitrage. The DG owners submit their hourly day-ahead prediction of available DG output while EV aggregators present their storage capacity based on the number of available EVs (use pattern/availability profile), battery capacity, charger ratings, and charging/discharging efficiencies.

III. PROBLEM FORMUATION

The stochastic multi-period OPF model which involves breaking of time-horizon into several time steps and scenarios is developed. During each time step and scenario, the network must obey typical OPF constraints independently [11][25].

A. Objective Function

The objective is to minimize the expected operational costs to the DSO (C_{DSO}) by optimally scheduling energy exchanges with the aggregators and DG owners such that energy from non-firm DGs is optimally utilized thereby reducing curtailment.

$$\min \boldsymbol{E}(\boldsymbol{C_{DSO}}) = \min \sum_{s=1}^{N_s} \pi_c \sum_{t \in T} (C_{s,t}^{gsp} + C_{s,t}^{nf} + C_{s,t}^{agg}) \quad \forall s \in N_s,\ \forall t \in T \tag{1}$$

$C_{s,t}^{gsp}$, $C_{s,t}^{nf}$ and $C_{s,t}^{agg}$ represent cost of transactions with main grid, non-firm DGs and aggregators respectively, and

$$C_{s,t}^{gsp} = \pi(t).P_{s,t}^{gsp}.\Delta t \tag{2}$$

$$C_{s,t}^{agg} = \sum_{i=1}^{N_{bus}} \sum_{agg=1}^{N_{agg}} \{\Pi_{sell}.P_{i,s,t}^{agg,ch} + \Pi_{buy}.P_{i,s,t}^{agg,dis}\}\,\Delta t \tag{3}$$

$$C_{s,t}^{nf} = \sum_{i=1}^{N_{bus}} \sum_{nf=1}^{N_{nf}} \{\pi(t).P_{i,s,t}^{nf} + \Pi_{curt}.P_{i,s,t}^{curt}\}\Delta t \tag{4}$$

N_{bus} =	Set of buses/nodes
N_{agg} =	Set of Aggregators
N_s =	Set of scenarios
i, j =	Index of buses
$\pi(t)$ =	Hourly electricity Price (£/MWh)
$P_{s,t}^{gsp}$ =	Active Power at *gsp* at time *t* at scenario *s*
Π_{sell} =	Sell Price to Aggregator (£/MWh)
Π_{buy} =	Buy Price from Aggregator (£/MWh)
Δt =	Optimization time step
$P_{i,s,t}^{agg,ch}$ =	Charging Power of aggregator at bus *i*, scenario *s*, at time *t*
$P_{i,s,t}^{agg,dis}$ =	Discharging Power of Aggregator at bus *i*, scenario *s*, at time *t*
Π_{curt} =	Curtailment penalty (£/MWh)
$P_{i,s,t}^{curt}$ =	Curtailed Power of non-firm DG at bus *i*, scenario *s*, at time *t*
$P_{i,s,t}^{nf}$ =	Power output of non-firm DGs at bus *i*, scenario *s*, at time *t*

B. Grid Supply Point (GSP) and Non-Firm DGs

The DSO is connected to the main grid via the grid supply point (gsp) [26]. DG connections to the distribution system are non-firm (index is nf) connections. The non-firm DG resources are modeled as supplying real and reactive power within their maximum capacity at each time *t* according to their power factor, that is:

$$0 \le P_{i,s,t}^{nf} \le P_{i,s,t}^{max} \qquad \forall nf \in N_{nf}, t \in T \tag{6}$$

$$0 \le Q_{i,s,t}^{nf} \le Q_{i,s,t}^{max} \qquad \forall nf \in N_{nf}, t \in T \tag{7}$$

C. Aggregators

Some of EV roles include load shifting, balancing services, flexibility, decreasing marginal cost of power, optimizing investment in power infrastructure and other ancillary services [27]. *EV* aggregators modeling is achieved by modifying the model of fixed energy storage system (ESS) to reflect features of aggregation. Effects of self-discharge and temperature on the *EV* batteries are assumed to be negligible. The model used in this work is expressed as follows for $\forall_{agg}, \forall_i, \forall_t, \forall_s$:

$$SOC_{i,s,t}^{agg} = SOC_{i,s,t-1}^{agg} - \left(\frac{\eta^{ch}\Delta t}{n(t).C_b} P_{i,s,t}^{agg,ch} + \frac{\Delta t}{\eta^{dis}.n(t).C_b} P_{i,s,t}^{agg,dis}\right) \tag{8}$$

$$SOC_{min}^{agg} \le SOC_{i,s,t}^{agg} \le SOC_{max}^{agg} \tag{9}$$

$$-P_{min,t}^{agg} \le P_{i,s,t}^{agg,ch} \le 0 \tag{10}$$

$$0 \le P_{i,s,t}^{agg,dis} \le P_{max,t}^{agg} \tag{11}$$

$$P_{i,s,t}^{agg,net} = P_{i,s,t}^{agg,ch} + P_{i,s,t}^{agg,dis} \tag{12}$$

$$P_{max,t}^{agg} = n(t).P_{EV}^{rated}(t) \tag{13}$$

$$n(t) = N_{EV}.\alpha(t) \tag{14}$$

$$Q_{max,t}^{agg} = \frac{P_{max,t}^{agg}.\sqrt{1-pf^2}}{pf} \tag{15}$$

$$SOC_{i,s,t-1}^{agg} = \frac{n(t-1).SOC_{i,s,t-1}^{agg} + (n(t)-n(t-1)).\widehat{SOC}}{n(t)} \tag{16}$$

(8) defines the SOC as a function of the previous SOC or initial SOC, the charging/discharging efficiency, charging/discharging rates, and battery capacity. (9) defines the restriction of the SOC. Constraints (10) and (11) limit the power that aggregators can charge/discharge according to the number of EVs available at any time *t.* (12) treats the net power of each aggregator as the combination of separate charging and discharging generators. The maximum power of each aggregator at each time *t* is defined by (13) where $P_{EV}^{rated}(t)$ is the EV's rated charger power and $n(t)$ is the number of EVs connected at time *t.* $\alpha(t)$ is $EV's$ availability factor at time *t.* (15) defines the maximum reactive power limits as a function of maximum aggregator power and fixed power factor. Equation (16) modifies the previous SOC in (8) to account for arriving EVs where $\widehat{SOC}$ is the initial SOC of arriving vehicles when $n(t) > n(t-1)$.

Four different types of aggregators used in this work are Residential, LongStay, Office and Public. The availability profiles of the aggregators are presented later in this work.

D. System Constraints: Equality and Inequality

This shall include real and reactive powers in the system, real and reactive power flows along the distribution line, voltage magnitude, real and reactive powers flowing in and out of the *gsp* and line limits [10].

E. Uncertainty Modeling and Scenario Generation

Stochastic optimization model minimizes the expected total cost of operation by the DSO as in (1) by including the uncertainty models of the following random variables - DG sources (wind and solar) and load demand. Stochastic programming assumes that the probability density function (PDF) of uncertain variables is known and assigned to expected outcomes [28]. Probabilistic scenario-based method shall be utilized in this work for generating a set of scenarios as used in [17], [29] and [30]. Five-year historical data of wind speed and solar irradiance were modeled into their respective PDFs and three probabilities for each variable were obtained. These independent outcomes combine to form twenty-seven scenarios. Accordingly, the PDFs of various variables are presented here [12], [31]:

a. **Wind Energy Model:** The Weibull probability density function (PDF) is used to describe uncertainties in wind speed. The Weibull PDF is expressed as:

$$f_v(v) = \left(\frac{\alpha}{\lambda}\right)\left(\frac{v}{\lambda}\right)^{(\alpha-1)} exp\left[-\frac{v}{\lambda}\right]^{\alpha} \qquad 0 < v < \infty \qquad (17)$$

Where α and λ represent the shape and scale parameter of Weibull distribution respectively and v is the wind. For this work, scale parameter = 8.042 while shape parameter = 3.024. The output power of wind generating units is determined by wind speed.

$$P_w(v) = \begin{cases} 0 & v \leq v_{in} \; and \; v > v_{out} \\ P_{wr}\left(\frac{v - v_{in}}{v_{rated} - v_{in}}\right) & v_{in} \leq v \leq v_{rated} \\ P_{wr} & v_{rated} \leq v \leq v_{out} \end{cases} \qquad (18)$$

where $P_w(v)$ is the output power of wind generator at speed v, v_{in} is the cut-in wind speed, v_{rated} is the rated wind speed, v_{out} is the cut-out power. These values are 4m/s, 14m/s and 25m/s respectively with $P_{wr} = 1MW$.

b. **Solar/PV Energy Model:** Solar output power is dependent on solar irradiance (G) which follows the normal PDF. The probability of solar irradiance with mean, μ_s and standard deviation σ_s can be written as:

$$f_{pv}(G) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[-\frac{(G-\mu_s)^2}{2\sigma_s{}^2}\right] \qquad (19)$$

The output power of solar PV as a function of solar irradiance is expressed as:

$$P_{pv}(G) = \begin{cases} P_{PVr}\left(\frac{G^2}{G_{std} \, x \, R_C}\right) & 0 \leq G \leq R_C \\ P_{PVr}\left(\frac{G}{G_{std}}\right) & G \geq R_C \end{cases} \qquad (20)$$

where P_{PVr} is the rated output power of PV unit (1MW), G_{std} is solar irradiance in a standard environment (1000W/m^2) and R_C represents certain irradiance point (120W/m^2).

c. **Load Model:** Uncertainty in load demand can be modeled by normal PDF as:

$$PDF(P_d) = \frac{1}{\sigma_d\sqrt{2\pi}} exp\left[\frac{-(P_d - \mu_d)^2}{2\sigma_d{}^2}\right] \qquad G > 0 \qquad (21)$$

Where μ_d is the mean value of load demand (and the forecast load value) and σ_d is the standard deviation.

A set 27 scenarios are obtained using equations (17) and (19) by dividing $f_v(v)$ and $f_{pv}(G)$ into a set of intervals as:

$$\pi_s = F(G_k \leq G \leq G_m) = \int_{G_k}^{G_m} f_{pv}(G)dv \qquad (22)$$

$$\pi_w = F(w_p \leq W \leq w_q) = \int_{w_p}^{w_q} f_v(v)dv \qquad (23)$$

Hence, the sum total of all scenarios' probabilities is equal to 1 i.e. $\sum_{c=1}^{N_s} \pi_c = 1$ (24)

IV. IMPLEMENTATION AND CASE STUDIES

Implemented in AIMMS [32], we have connected several non-firm DGs and aggregator types on a test system. The test system is a modified IEEE-33 Bus, 12.66kV radial distribution system (network parameters adapted from [33]).

Table 1: EV Aggregator Parameter

Description	Value
Battery Capacity	30kWh
Charger Power	6.6kW
Charge efficiency	0.9
Discharge Efficiency	0.9
Initial SOC	0.65
Minimum SOC	0.35
Maximum SOC	0.95
Power Factor	0.95
Sell Price (to Aggregator)	£233/MWh
Buy Price (from Aggregator)	£170/MWh
Aggregator Size	200
Curtailment Price	£240/MWh

V. DISCUSSION OF RESULTS

The following four subcases are investigated as presented in Table 2. The table also presents the results for all 27 scenarios in terms of cost and curtailment.

Table 2: Sub-cases for Stochastic Cases

Case	Non-Firm DGs	Aggregator	Curtailment Penalty	Minimum Expected Cost (£)	Average Curtailment (MWh)
1	Yes	No	Yes	13,576.36	19.05
2	Yes	Yes	Yes	13,420.55	11.261
3	Yes	No	No	13,244.23	904.069
4	Yes	Yes	No	13,053.75	910.176

A. Overall Costs and Curtailment

Here, the aggregators used are public and residential. In the results in Table2, curtailment is only possible during peak hour generation times between 14:00 and 18:00. The network can fully accommodate production of energy during the other hours. Table 2 shows the minimum expected cost of operation incurred to the DSO in equation (1) across all 27 scenarios. As seen in Figure 1, DSO trades with DGs, aggregators and the TSO all at wholesale energy prices taken from Nordpool [34]. For cases 3 and 4, the DSO minimizes its cost by buying lower energy from the non-firm DG's total 2385.37MWh for all scenarios. It is seen in Table 2 that for Case 2 having both the ability to transact with aggregators and maintain a curtailment penalty will result in maximizing utilization of DGs in the network. However, this needs not necessarily result in minimum expected operational costs for the DSO. DSO can further be incentivized with aggregators through more favourable pricing schemes. In this paper, DSO transacts with aggregators at the wholesale energy prices.

B. Aggregator's Impact Evaluation

In this section, all four aggregators under each scheme are the same. We hereby present all four types of aggregator's availability patterns:

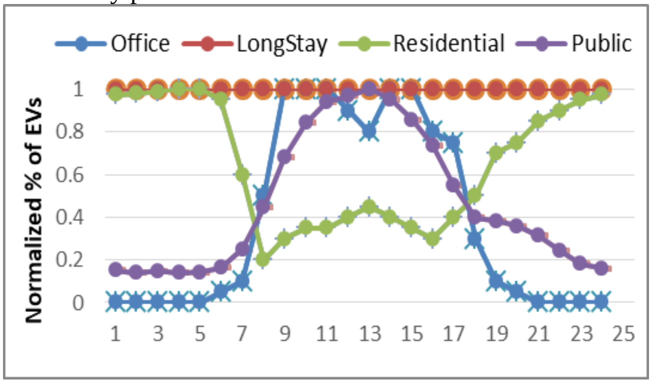

Figure 2: Availability Factors of EVs

The impact of each set is then tested and results are presented.

Table 3: Curtailment and Minimum Expected Cost of Operation

Case	Office	Public	LongStay	Residential
Curtailment (MWh)	8.04	8.99	12.21	14.77
Cost(£)	13,359	13,421	13,473	13,437

With reference to Table 3, residential aggregators had the least reduction of curtailment. The reason being that fewer EVs are connected at residential homes during afternoon peak hours of renewable generation. The LongStay aggregators do have maximum number of EVs available throughout the 24-hour optimization period, hence cannot charge during afternoon peak hours of maximum renewable generation. The office aggregator is the best in terms of curtailed power and operating cost. This is due to high availability of EVs during a period of peak renewable generation. In addition, a number of EVs are still available during evening peak demands to sell energy to the DSO at a lower market price. Finally, the public aggregator is second best after office. This result is very similar to Office's case in which EVs are available for charging during peak generation hours, therefore non-firm curtailment is less.

C. Voltage Regulation

EV aggregators usually balance the power system by buying (charging) electricity from the DSO during peak generation while keeping voltage within acceptable range and supplying (discharging) when there is shortage of supply. This price-induced balancing also leads to voltage regulation. We hereby present the three cases thus:

1. **Passive Distribution Network**: No DGs and Aggregators applied to the network. Lowest voltages found at the end of feeders (bus 18 and 33), as expected.

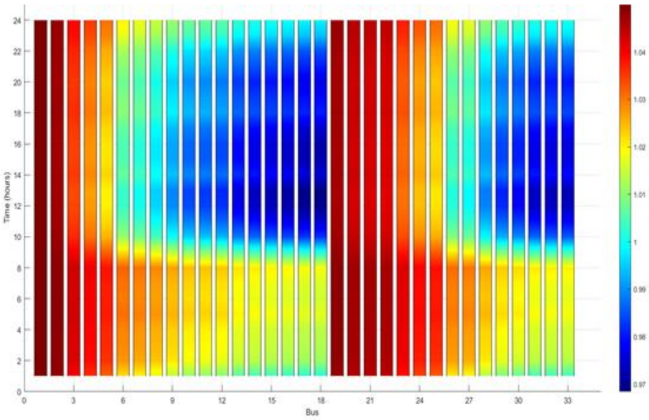

Figure 3: Voltage profile without the Aggregators and DGs

2. **Active Distribution System with High Penetration of DGs:** Integration of DGs results in higher voltages. There are significant reverse power flows in the network but all within 0.95 and 1.05pu.

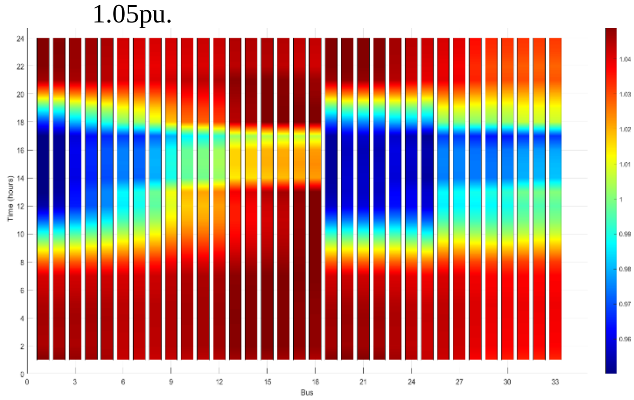

Figure 4: Voltage Profile with only DGs

3. **Case (ii) above with aggregators**: This contains DGs and aggregators and is also characterized by significant reverse power flows. At early hours when prices are low, the DSO imports more energy from the grid for aggregators to charge. Later in the day when market prices are high, the DSO uses the aggregator energy to meet electricity demands in the network, thereby keeping voltages within their limits. These voltage profiles demonstrate how price-controlled demand can be used to regulate bus voltages.

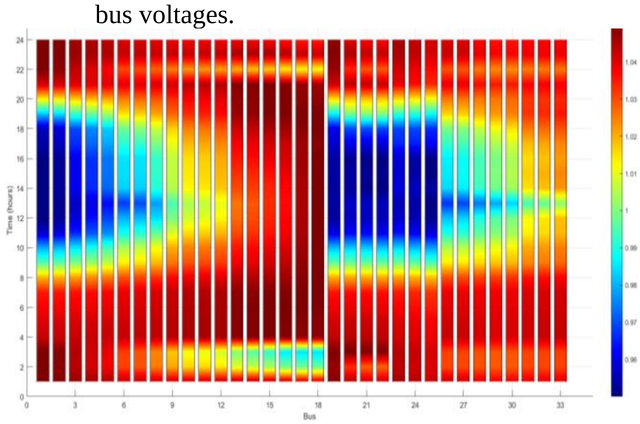

Figure 5: Voltage Profile with Aggregators and DGs

VI. CONCLUSION

This research has been able to optimally solve a developed stochastic model containing high levels of renewable energy and various aggregators for cost minimization and curtailment reduction. The stochastic model is a 27 scenario-based, multi-period model that involve uncertainties in renewable energy generation and power demanded. The DSO, being guided by the day-ahead electricity price, is able to minimize expected operational cost by trading with the grid (TSO), DGs and the aggregator and scheduling curtailment of non-firm DGs in a cost-effective way. Results show that Office aggregators where availability profiles closely match renewable generation are most effective in reducing both curtailment and expected cost of operation. Finally, the price-controlled demand was used to regulate voltage level. This is seen as the DSO imports more energy from the grid at low market prices and buys from the aggregator at high market prices.

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