Cost/Benefit Assessment of a Smarter Distribution System with Intelligent Electric Vehicle Charging

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***Abstract*—In the near future, with more distributed generators connected and new demands arising from the electrification of heat and transport in the distribution networks, infrastructure will become ever more stressed. However, building costly new circuits to accommodate generation and demand growth is time-consuming and environmentally unfriendly. Therefore, active network management (ANM) has been promoted in many countries, aiming to relieve network pressure. Previous research in ANM was focused on distribution areas with significant renewable penetration, where ANM reduced network pressure through significantly enhanced generation curtailment strategies rather than adopting traditional asset investment.**

This paper proposes the use of electric vehicles (EVs) as responsive demand to complement network stress relief that was purely based on generation curtailment. This is achieved by allowing EVs to absorb excessive renewable generation when they cause network pressure, and it thus can provide additional measures to generation curtailment strategies. The approach is illustrated on a practical extra-high voltage distribution system. The analyses clearly demonstrate the combined management of demand and generation is superior to previous sole generation management. The combined management strategy can achieve 7.9% improvement in utilization of renewable energy, and subsequently increase the net investment profit by £566k.

***Index Terms*—active network management, demand side management, electric vehicle, network pressure, renewable energy generation.**

I. Introduction

THE UK has signed up to the EU Renewable Energy Directive, which includes a UK target of 15% energy from renewables by 2020. The target demands a seven-fold increase in energy consumptions from renewables from 2008 level [1]. Significant of renewable energy generators are expected to be connected to the existing distribution network. The distribution networks are traditionally designed to distribute power from grid supply points to end customers. They have very limited capacity to accommodate significant renewables. This can lead to severe network pressure and significant energy losses during generation peak times, particularly for areas that are dominated by renewable generation. The traditional way to provide the extra network capacity is to reinforce the capacity of existing circuits or to construct new circuits, which is expensive, time-consuming, and environmentally unfriendly.

Active network management (ANM) [2] has emerged as a cheaper alternative to the traditional network investment to accommodate growing generation and demand. Through better utilization of the existing network capacity, ANM can strike the right trade-offs between building new assets and enhancing system operational performance [3-10]. In generation dominated area, i.e. network pressure caused by significant renewable development, ANM, like active generator output curtailment strategy, is more economic than network reinforcement investment when accommodating growing distributed generators (DGs) [11]. Several active control methods have been presented in [4, 12-14]. A multi-period AC optimal power flow technique is proposed to maximize wind power capacity in [4]. Active power flow management is applied in [12], based on logic control for trimming and tripping of regulated non-firm generation to control power flow. Paper [13] uses artificial intelligence technique based constraint programming to automatically manage DG real power outputs in medium voltage distribution networks. An autonomous regional active network management system is introduced in [14] to reduce network pressure through using enhanced generation curtailment strategies. However, previous efforts in these papers only investigate the value of ANM in terms of economic generation curtailment, but they do not consider the benefits from demand side management (DSM) particularly from flexible demand, like electrical vehicles (EVs).

DSM is implemented to dynamically balance the demand between peak times and load curve valleys, thus reducing network planning and operation cost [15-17]. EVs, which are regarded as energy storage, can smooth the intermittency of renewable energy resources, such as wind power. If EV charging can be controlled to coincide with lull periods in demand, this would not only avoid exacerbating peak loads but also accommodate excessive wind power. The potential benefits of "wind-EV" complementation are discussed in [18, 19]. According to [20], DSM programs can be classified into price-based [21, 22] and incentive-based [23-25]. Price

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mechanisms in the form of time-of-use (TOS) electricity tariffs are employed in [21] to encourage commuters to recharge EVs during off-peak hours. Paper [22] shows a novel method to plane EV charging, which is achieved by electricity price first and then be constrained with electricity grid constraints, both voltage and power. A DSM strategy that takes into account customers' preferences, comfort levels, and load priorities is proposed in [24] to accommodate EV charging while keeping the peak demand unchanged. Paper [25]establishes a single EV charging demand model, and then employs queuing theory to describe the behavior of multiple EVs.

This paper applies DSM achieved through smart charging of EVs on the existing ANM. The proposed control algorithm focuses on the technical aspects of incentive-based DSM. The optimal EV response across the entire network is determined in time sequence in order to alleviate network pressure points. The demonstration results show that when DSM is considered, the network pressure can be alleviated before generation curtailment. A substantial reduction of up to 7.9% in renewable energy curtailment can be realized. …….uncertainty energy prices

This paper has the following four key contributions.

1) DSM with EV utilization in time sequence is applied on the existing ANM; …..

2) It determines the impact of different time window scale for intelligent EV charging on distribution network operation benefits and costs;

3) It designs alternative planning strategies for distribution systems where both intelligent EV charging and economic generation curtailment are exercised for the largest profits.

The paper is organized as follows. Section II introduces a model of existing ANM without DSM. Section III describes the improved ANM with DSM. Section IV discusses the case study of 33kV Aberystwyth network. Section V assesses the cost/benefit of the combined management of demand and generation in distribution network and its influence on network planning. Finally, the conclusion is drawn in Section VI.

II. Constraint Management of Existing ANM without DSM

Traditional constraint management for network pressure in distribution network follows the last-on-first-off (LOFO) rule [26], where the last-on distributed generator (DG) will be the first to be tripped off or curtailed once line overloading is detected. However, sometimes, the last-on DG may not contribute to remove the overloading, which results in unnecessary wasted energy. To overcome the disadvantage, ANM has been developed. Within various ANMs, a project called autonomous regional active network management system (AuRA-NMS) was deployed in the UK in 2006 [27, 28]. It allows real-time states to be used to select the most sensitive bus-bar to relieve network pressure, which could eliminate stress with the least amount of generation curtailment or load shedding. The optimal decision of existing AuRA-NMS is formulated as the following linear programming problem [27]:

Objective:

$$min\left(\sum_{i\in NG}\alpha_i \Delta P_{gi}+\sum_{i\in ND}\beta_i \Delta P_{di}\right) \quad (1)$$

Subject to:

$$\sum_{i\in NG}(P_{gi}-\Delta P_{gi})-\sum_{i\in ND}(P_{di}-\Delta P_{di})=0 \quad (2)$$

$$\left|\sum_{i=1}^{N} S_{li}\cdot(P_{gi}-\Delta P_{gi}-P_{di}+\Delta P_{di})\right| \le P_l^{max},\ l\in NB \quad (3)$$

$$P_{gi}^{min}\le \Delta P_{gi}\le P_{gi}^{max},\ i\in NG \quad (4)$$

$$0\le \Delta P_{di}\le P_{di},\ i\in ND \quad (5)$$

where at the i^{th} bus-bar, α_i is coefficient of generation curtailment, β_i is coefficient of load shedding, P_{gi} is power generation, P_{di} is the load demand, ΔP_{gi} is generation curtailment, ΔP_{di} is load shedding, P_{gi}^{min} is the lower limit of generation output, P_{gi}^{max} is the upper limit of generation output, P_l^{max} is the maximum power flow of the l^{th} line and S_{li} is an element in the sensitivity matrix S of line flow to nodal power injection. P_l^{max} *NB*, *NG*, and *ND* are the sets of branch, generation, and load demand, respectively.

Power transfer distribution factor (PTDF) is a sensitivity matrix of line active power flow with respect to nodal power injection. When an overloaded state is detected, the most overloaded line *lm* will be found first. Then PTDF is introduced as a reference matrix to select the most sensitive bus-bar, which has the largest impact on line *lm*. Based on the PTDF, the generation curtailment ΔP_{gi}, which can be used to quantify the operational benefit of AuRA-NMS constraint management, is derived as

$$\Delta P_{gi}=\min\left\{\frac{|P_{lm}-P_{lm}^{max}|}{PTDF(lm,gi)-PTDF(lm,si)},\ P_{gi}\right\},\ i\in NG \quad (6)$$

where *si* is the slack bus, P_{lm} is the power flow on line l_m, and P_{lm}^{max} is the line rating on line l_m. It is worth noting that the operational benefit in the existing AuRA-NMS is obtained only through generation curtailment and neglects the potential operational benefit from the demand side.

III. Proposed Control Algorithm for ANM with DSM

To improve the utilization of renewable energy and increase net investment benefit, in our proposed control algorithm, EV charging strategy is exemplified as DSM. This approach is taken to evaluate potential operational benefit from the demand side. This section is separated into two parts. After indicating constraints for intelligent EV charging in section A, the operation of DSM (intelligent EV charging) is explained in section B.

A. Constraints for intelligent EV charging

In order to calculate the lower/upper limits for EV charging, two conditions are assumed in the proposed algorithm:

1. Total electricity consumption before and after DSM on each node remains unchanged.
2. EV load shifting capability is predefined, limited by EV battery capacity, assumed travel behavior, *etc*.

The first assumption can be mathematically represented as

$$\sum_{i\in ND} P_{di} = \sum_{i\in ND} P_{d_n i} \quad (7)$$

where $P_{d_n i}$ is the new load demand at bus i after load shifting. The predefined EV load shifting capability in the second assumption can be described as

$$\Delta P_{di,t} = \min\left\{ \frac{|P_{lm} - P_{lm}^{max}|}{LTDF(lm,di) - LTDF(lm,si)}, EV_{di,t} \right\}, i \in ND \quad (8)$$

where at the i^{th} bus-bar and in t^{th} sequence, $\Delta P_{di,t}$ is the required reductive/incremental amount of EV load demand to eliminate network pressure, $EV_{di,t}$ is the flexible amount of EV demand, and LTDF (load transfer distribution factor) is a sensitivity matrix of line active power flow with respect to nodal demand. Since load is regarded as negative generation, LTDF can be derived from PTDF. The lower/upper limits of $EV_{di,t}$, denoted as $[C_{t,min}\ C_{t,max}]$, are considered over a 24-hour period and are determined by three factors [22, 23, 29, 30]:

1. Number of EVs.
2. EV battery characteristics.
3. Road trip limitations.

1) Number of EVs

The number of EVs on a specific bus-bar is calculated according to EV penetration rate and the corresponding customer number. EV penetration rate is assumed to be 0.675 per customer from year 2030 to 2050 [31]. Customer number on the i^{th} bus-bar (CN_i) can be expressed as

$$CN_i = \frac{D_i \cdot \eta_i}{ADD_i}, i \in ND \quad (9)$$

where D_i is the annual load demand, η_i is the percentage of domestic customers [32], and ADD_i is the average domestic electricity consumption [32]. Numbers of EVs on 12 different bus-bars are shown in detail in Table 1.

TABLE 1
NODAL EV OWNERSHIP IN THE NETWORK

Bus Bar	Yearly Load Demand (MWh)	Domestic percentage	Average Domestic consumption (KWh)	Customer Num.	EV Num.
Bow street	26011	46.61%	5652	2145	1448
Machynlleth1	17109	43.39%	4946	1501	1013
University College Wales	29496	46.61%	5652	2432	1642
Aberdovey	15775	46.92%	5134	1442	973
Tywyn	23929	46.92%	5134	2187	1476
Fairbourne	14816	46.92%	5134	1354	914
North Road	30644	32.60%	3952	2528	1706
Aberystwyth	29926	46.61%	5652	2468	1666
Parc Y Llyn	35785	48.95%	4361	4017	2711
Llanilar	12792	46.61%	5652	1055	712
Rhydlydan	5621	48.95%	4361	631	426
Rhydlydan ST1	3385	48.95%	4361	380	257

2) EV battery characteristics

Typical EV battery capacity (B_c) in the UK is Nissan Leaf characterized by 24kWh. To avoid damage and premature aging, there are limitations on the battery state-of-energy [22] as shown below:

$$\delta_{min} B_c \le S_{k,t} \le \delta_{max} B_c \quad (10)$$

where $S_{k,t}$ is the state-of-energy of vehicle k at timeslot t. The minimum (δ_{min}) and maximum (δ_{max}) coefficients of the battery capacity are set to be 0.2 and 0.9, respectively.

3) Road trip limitations

The use of an EV at each timeslot within 24 hours can be obtained from [29] as shown in Fig. 1. The average electricity consumption of an EV in use is 2.1 kW [23]. When an EV is parked at a charge station, the vehicle is assumed to charge immediately at the maximum charging rate of 4 kW. Since the operation of ANM is executed on each bus-bar rather than each customer, this paper considers total EVs on each bus-bar instead of individual EV separately.

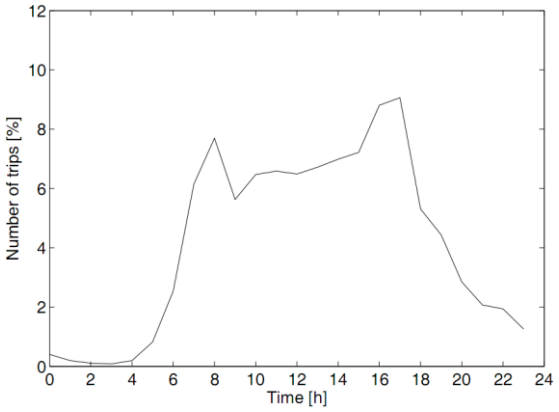

Fig. 1. Percentage of trips by EV at each hour

To guarantee sufficient energy for the next hour trip, the battery state-of-energy S_t of an EV should fall within the minimum and maximum energy range. For a large number of EVs (N) on a bus-bar, the total state-of-energy of batteries varies in the range of $[S_{t,min}, S_{t,max}]$. The upper ($C_{t,max}$) and lower ($C_{t,min}$) limits of EV charging at timeslot t can be expressed as:

$$C_{t,min} = max\{P_{dr,t+1} + N\delta_{min}B_c - S_{t-1,max}, 0\},\ 1<t\le 24 \quad (11)$$

$$C_{t,max} = min\{N\delta_{max}B_c - S_{t-1,min},\ P_{ch} \cdot N_{undrv,t}\},\ 1<t\le 24 \quad (12)$$

$$S_t = S_{t-1} + C_t - P_{dr,t},\quad 1<t\le 24 \quad (13)$$

$$S_{1,min} = N\delta_{min}B_c + P_{dr,2} \quad (14)$$

$$S_{1,max} = N\delta_{max}B_c \quad (15)$$

where $S_{t-1,min}$ ($S_{t-1,max}$) is the minimum (maximum) state-of-energy at timeslot t-1, $P_{dr,t+1}$ is total electricity consumption of all EVs on the bus-bar over the next timeslot t+1 due to driving, P_{ch} is the maximum charging rate per vehicle when it is stopped, $N_{undrv,t}$ is the number of stopped EVs at timeslot t, $S_{1,min}$ ($S_{1,max}$) is the min (max) energy-of-state at the end of 1st hour, and $P_{dr,2}$ is the driving electricity consumption in the 2nd hour.

In order to derive the lower/upper limits of EV charging ($C_{t,min}$ and $C_{t,max}$), some initial conditions should be clarified for the energy-of-state S_t as listed in (14) and (15). The unknown

S_t and C_t in (11) and (12) can then be derived from each other according to the recursive relationship in (13).

B. Operation of EV charging strategy

In the proposed control algorithm, load demand and generation profiles are updated every hour. The intelligent EV charging follows the time-window schedule. M-time-window means that in time sequence *t*, load shifting can be made in the following *M*-1 hours, i.e. from *t*+1 to *t*+*M*-1. When no network stress is detected in *t*, the check system will move on to sequence *t*+1 and the dispatch of EV charging in *t* keeps unchanged. Otherwise, intelligent EV charging starts to work before the check system moves on to the next sequence.

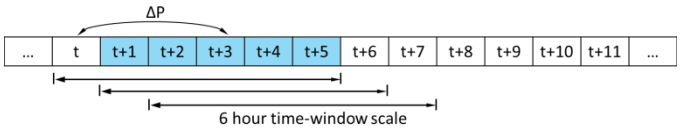

Fig. 2. Schematic illustration of 6-hour time-window

In proposed ANM with DSM, when network pressure is detected, the most overloaded line (*lm*) will be found in the same way as that in existing ANM without DSM. According to LTDF, the most sensitive node with maximum absolute LTDF value will be picked out. The value of LTDF could be either negative or positive for increasing or decreasing load demand, respectively. According to (8) and by using LTDF, the ideal load shifting quantification $\Delta P_{di,t}$ can be calculated to eliminate network pressure. The next step is to find a proper timeslot in the time-window scale to exchange $\Delta P_{di,t}$. For example, when the time-window scale is assumed to be 6 hours, the best timeslot is chosen within the shadow grids as shown in Fig. 2. By ranking EV flexibility at these timeslots, where EV flexibility is the difference between original EV charging amount and EV charging boundary ($C_{t,max}$/$C_{t,min}$), the most suitable timeslot can be chosen. If timeslot *t*+3 has the maximum EV flexibility, the exchange of $\Delta P_{di,t}$ should be done between timeslot *t* and timeslot *t*+3 in Fig. 2. If the network pressure cannot be totally eliminated, the program will look into the second most sensitive node to make further load shifting. The loop will carry on until there is no available EV left for load shifting. After that, generation curtailment is executed as mentioned in section II to eliminate the remaining network pressure. The corresponding flowchart for proposed ANM constraint management with DSM is shown in Fig. 3.

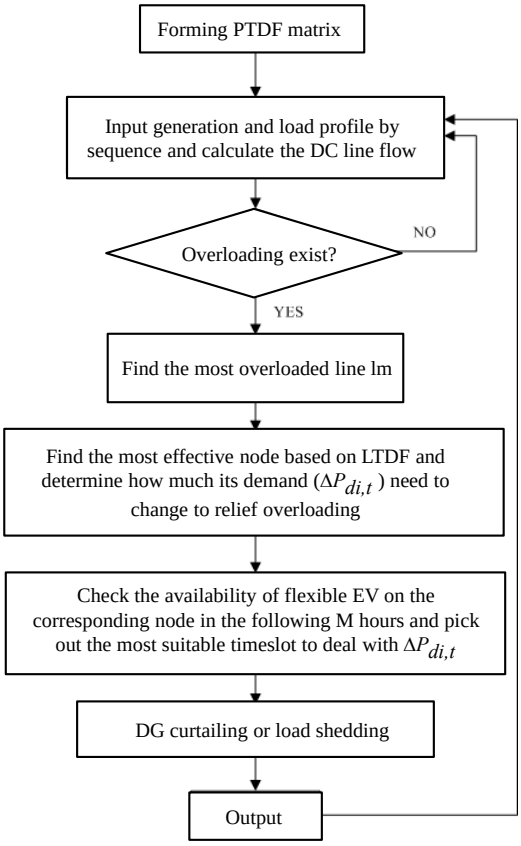

Fig. 3. Flowchart of ANM constraint management with DSM

IV. Case Study of ANM with DSM

To analyze the benefit of proposed ANM with DSM, a 47-node network is studied. In section A, a practical test system of ANM with DSM is introduced and its load profile is forecast. In section B, the corresponding simulation results are discussed.

A. A practical test system of ANM with DSM and EV demand forecast

The test system, Aberystwyth 33kV network, is a practical 132/33kV distribution network in the UK [27] and its simplified single line topology is shown in Fig. 4. For the test system, the hourly 33kV load demand and DG output are available in year 2006, where there are 8760 operating states in total. The load profile in year 2006 mainly contains classical loads, namely domestic, commercial, and industrial electricity consumption. Load demand in the Aberystwyth area is not expected to increase in the short and medium term. Hence, all future classical loads are assumed invariant from 2006 to 2029. When more EVs and heat pumps are connected, a large amount of flexible load demand will be added to the classical loads. In order to use the data of year 2006-2050 to simulate the test system, the forecast of load demands of 2030-2050 are required.

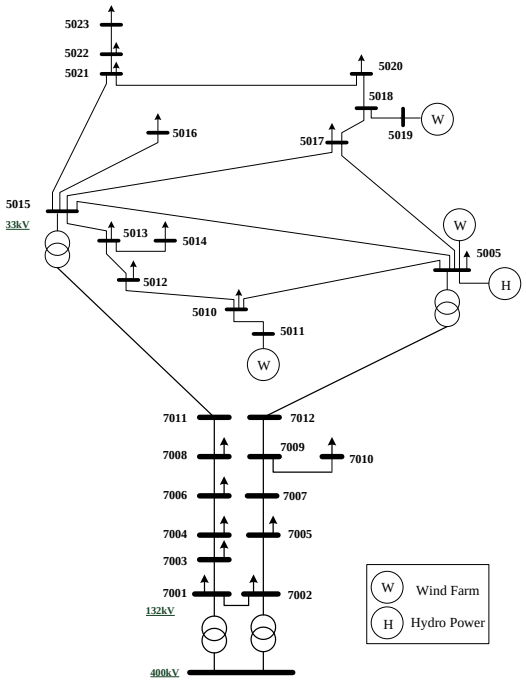

Fig. 4. Single diagram of the 132/33kV network

New added EV demand on each bus-bar can be estimated analytically based on the customer number ratio in that area, which is the ratio of the customer number (CN_i) to the total population in the UK [33]. With demand profiles (database in DECC summary) for the whole UK and customer ratio of each bus-bar, we can allocate the EV load demand of the whole country to the test system.

B. Time-series simulation of the test system

Power flow calculations are carried out for the 8760 operating states in sequence. After simulation, the generation curtailment results are counted. It is assumed that the duration of each generation curtailment is one hour. The total generation curtailments are identified in the whole year. Overloading mainly occurs on the power flow of line 5015-5017, 5010-5012, and 5018-5017, because of the new DG integration. When line overloading occurs in some operating states, for the year 2030, ANM without DSM needs to curtail renewable energy by 1790.74 MWh. When DSM is considered, however, the generation curtailment reduces dramatically as shown in Fig. 5. The reduction reaches up to 7.9% and its average value is around 7.6%. In Fig. 5, two phenomena are worth noting. First, in most situations, the generation curtailment is found to decrease when time-window scale increases. The 24-hour time-window scale has the least generation curtailment. Thus, we argue that larger time-window scale can give better perspective of the network condition to help make a smarter load shifting decision. Second, small fluctuations appear in the curve. ANM with DSM is used to minimize the generation curtailment in one particular hour within a fixed time-window scale. The optimization simulation is done in sequence. The operation in earlier hours may increase the power flow in later hours and make network congestion in later hours more severe. Therefore, the increased generation curtailment in later hours may be bigger than the saved generation curtailment in earlier hours, which makes the total annual generation curtailment more in the end and leads to the curve fluctuation.

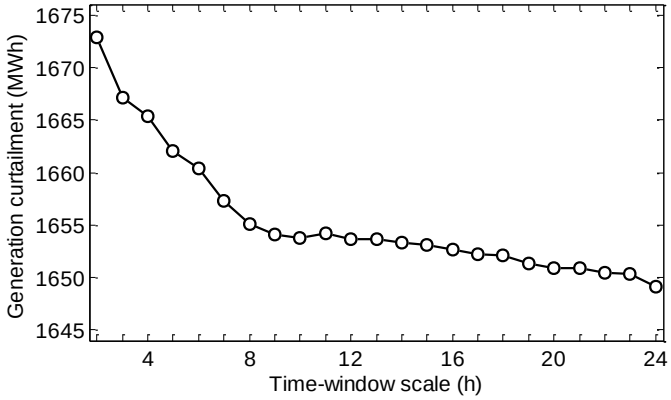

Fig. 5. Generation curtailment of ANM with DSM under different time-window scales

In ANM without DSM, the most serious congestion happens at 10:00 a.m. on the 340th day of the year 2030. Thus, data on this day is chosen to analyze the change in load curve due to DSM. ANM with DSM goes through all bus-bars to do load shifting according to their LTDF ranking before generation curtailment. Since one node load shifting is limited and always not enough to eliminate line overloading, we analyze the load shifting of the entire network as shown in Fig. 6.

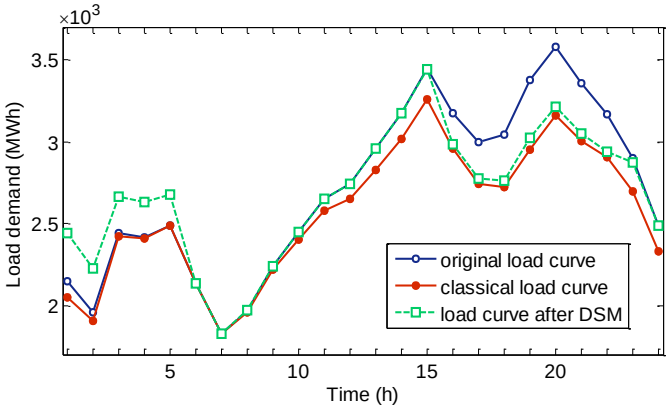

Fig. 6. EV re-dispatch on peak generation curtailment day

The generation curtailments of ANM with and without DSM are displayed in Table 2. Without DSM, the total generation curtailment of the 340th day is 28.7 MWh. The value could be reduced by 12% (namely 3.5 MWh) with DSM. In Fig. 6, the difference between the original load curve (blue) and classical load curve (red) reveals the original EV charging, and the difference between classical load curve (red) and load curve after DSM (green) is re-dispatch of EV charging in 24-hour period. In the first 5 hours (from 0:00 to 5:00), the EV demand is increased to reduce the generation curtailment. The increasing EV demand mainly comes from load shifting accumulated from the previous day or the later hours. In the following 10 hours (from 5:00 to 15:00), the load curve after DSM matches the original load curve in Fig. 6. However, one should note that this does not mean there is no load shifting on

individual nodes in Fig. 6 and one can see that the curtailment values still have changes in these hours in Table 2. From the 16th hour on (from 15:00 to 24:00), compared with the original load curve, the load curve after DSM decreases dramatically, which is due to the slight line congestion detected in these hours. The shaved EV demand is moved to the timeslots that need larger load demand to alleviate network pressure. Although the generation curtailment has a small increase at 22:00 in Table 2, the total curtailment of the whole 340th day is reduced.

TABLE 2
GENERATION CURTAILMENT COMPARISON WITH AND WITHOUT DSM

Time	Without DSM (MWh)	After DSM (MWh)
1:00	1.35	0.64
2:00	0.38	0.00
3:00	0.30	0.00
4:00	0.00	0.00
5:00	2.57	1.98
6:00	0.75	0.75
7:00	0.98	0.98
8:00	2.47	1.98
9:00	4.31	3.86
10:00	4.46	4.07
11:00	2.27	1.90
12:00	4.31	3.98
13:00	1.97	1.67
14:00	1.69	1.73
15:00	0.88	1.18
16:00	0.00	0.00
17:00	0.00	0.00
18:00	0.00	0.00
19:00	0.00	0.00
20:00	0.00	0.00
21:00	0.00	0.00
22:00	0.01	0.44
23:00	0.00	0.00
24:00	0.00	0.00
Total	28.69	25.16

V. COST/BENEFIT ASSESSMENT OF ANM WITH DSM AND NETWORK PLANNING

In this section, the impact of DSM on the optimal trade-off between operational benefit and network investment cost is discussed. The alternative planning strategies for smart distribution system are also recommended.

A. Wind farm repowering and load profile forecast

Considering the life expectancy of existing wind-farms, the year they were commissioned, the potential for increasing land use, and the potential for increasing turbine size, the expansion size and time of repowering wind farms are investigated in [26]. Since the repowering in 2018 has already reached the maximum wind blade size level, the wind turbines cannot be expanded any more. Therefore, the wind generation profile will stay the same as that of 2018. The load profile from 2011 to 2050 was forecast in section IV.

B. Benefit and cost category

For each investment option, the operational benefit considered is from the annual generation curtailment reduction as shown:

$$B_y = EP_y \cdot GC_y \quad (16)$$

where in the year y, B_y is the operational benefit, EP_y is the electricity price, and GC_y is the generation curtailment reduction.

The network investment cost considered in network planning mainly includes primary asset investment, ANM, and DSM as shown:

$$C_y = AC_y + ANM_y + DSM_y \quad (17)$$

where in the year y, C_y is the network investment cost, AC_y is the cost of asset investment, ANM_y is cost of investing ANM, and DSM_y is the cost from DSM.

For the primary asset investment, the time to invest new lines in network is determined by the year the wind farm is upgraded and the EV demand connected. The detailed information is listed in Table 3 [26]. For existing ANM without considering DSM, its cost is £700k for the test system and its lifetime is 20 years [27]. In order to test the feasibility of the constraint programming method for power flow management in ANM, a software prototype was recently, developed to run on commercially available substation computing equipment [11]. Hence, the cost of ANM consists of hardware and software. For DSM, its cost estimation, however, varies significantly between countries and even between networks in one country. Therefore, it is difficult to determine the specific cost of DSM. However, one should note that since existing ANM already has the ability of remote measurement and monitoring, which can remote monitor the EV consumption, DSM can be integrated into the software in ANM. Therefore, in our proposed ANM with DSM, the cost of integrating DSM is minimized.

TABLE 3
TIME AND COST OF PRIMARY ASSET INVESTMENT

Number	Right of Way	Year	Cost (£m)	Present Value (£m)	Lifetime (years)
Asset 1	5015-5017 5017-5018	2013	1.33	1.14	40
Asset 2	5010-5012 5012-5013	2018	3.13	1.94	40
Asset 3	5017-5018	2030	1.25	0.33	40

After the operational benefit and investment cost are obtained, the internal rate of return (IRR) is used to compare the profitability of each planning strategy. The higher an option's IRR, the more desirable it is to be undertaken. It is calculated by setting the option's net present value (NPV) [34] to be zero as:

$$NPV = \sum_{y=2011}^{2050} \frac{(B_y - C_y)}{(1+IRR)^{(y-y_0)}} = 0 \quad (18)$$

where y_0 is the year 2011.

C. Investment options

The exhaustive list of investment options in Table 4 reflect four potential planning strategies, listed below, that distribution network operators (DNOs) might adopt in the light of increasing renewable penetration and EV demand.

1) Invest only in network primary assets.
2) Invest only in the ANM.
3) Invest both in network assets and ANM.

TABLE 4
EXHAUSTIVE INVESTMENT OPTIONS

Plan No.	Investment detail	Plan No.	Investment detail
1	2 lines in 2013	9	ANM in 2011& 2031+2 lines in 2013
2	2 lines in 2018	10	ANM in 2011& 2031+2 lines in 2018
3	1 line in 2030	11	ANM in 2011& 2031+1 line in 2030
4	2 lines in 2013+2 lines in 2018	12	ANM in 2011& 2031+2 lines in 2013+2 lines in 2018
5	2 lines in 2013+1 line in 2030	13	ANM in 2011& 2031+2 lines in 2013+1 line in 2030
6	2 lines in 2018+1 line in 2030	14	ANM in 2011& 2031+2 lines in 2018+1 line in 2030
7	2 lines in 2013+2 lines in 2018+1 line in 2030	15	ANM in 2011& 2031+2 lines in 2013+2 lines in 2018+1 line in 2030
8	ANM in 2011& 2031		

D. Network planning considering electricity price uncertainty

From year 2010 to 2050, energy price will fluctuate as well as the electricity price. Based on two key global drivers (the speed of global economic recovery and the extent of globally coordinated environmental action), Ofgem's Project Discovery - Energy Market Scenarios projects electricity price from year 2010 to 2025 in four different scenarios, namely GREEN TRANSITION, SLOW GROWTH, GREEN STIMULUS, and DASH FOR ENERGY [35]. To investigate the impact of electricity price uncertainty, we adopt the wholesale electricity price from year 2010 to 2025 in [35] and assume the wholesale electricity price from year 2026 to 2050 will be same with year 2025.

By applying electricity price in (16-18), the corresponding IRR of each investment option is calculated. Fig. 7 shows the IRRs in ANM without DMS. In Fig. 7, the highest IRRs are obtained in option 8 for all scenarios (26.34% in SLOW GROWTH, 26.18% in GREEN TRANSITION, 29.77% in DASH FOR ENERGY, and 24.56% in GREEN STIMULUS). Option 11 is comparable to the most profitable option 8. Fig. 8 shows the IRRs in proposed ANM with DSM. The curve tendency in Fig. 8 is similar to that in Fig. 7. Option 8 still gets the highest profit in four scenarios. However, its largest IRR reaches 26.36%, 26.19%, 29.79% and 24.58% in scenario SLOW GROWTH, GREEN TRANSITION, DASH FOR ENERGY and GREEN STIMULUS, respectively. Fig. 7 and Fig. 8 give the recommendations in distribution network planning. However, in these two figures, it is difficult to see the increased benefit from applying DSM.

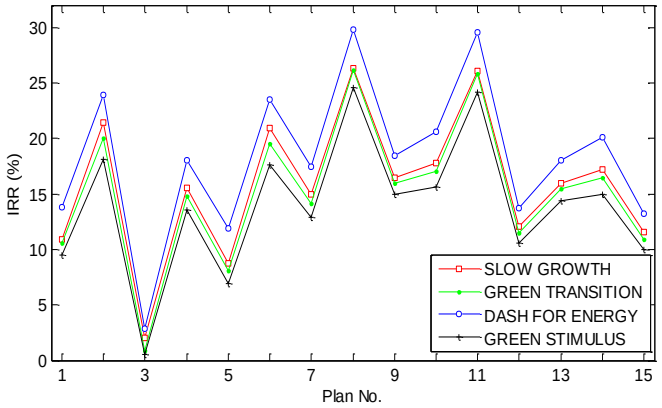

Fig. 7. Options' IRRs in ANM without DSM

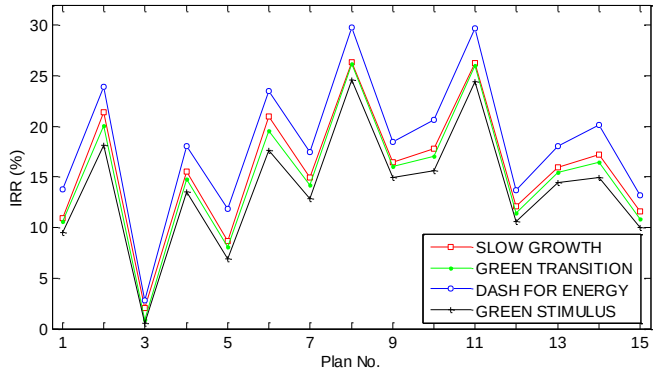

Fig. 8. Options' IRRs in proposed ANM with DSM

Fig. 9 shows the increased operational benefit from adding DSM to ANM. For each investment option, the increased benefit is calculated by comparing NPVs in ANM with and without DSM. In order to obtain NPVs, the IRR in (18) is set to be 6.9% [36] for all investment options. In Fig. 9, options 8 to 15 show increased benefit due to DSM, whereas options 1 to 7 show no increased benefit since they are only line investment. Option 11 (AuRA in 2011& 2031+1 line in 2030 in Table 4) gets the largest increased benefit from DSM (£530k in SLOW GROWTH，£478k in GREEN TRANSITION, £566k in DASH FOR ENERGY, and £463k in GREEN STIMULUS). Under different scenarios, the increased benefit in same investment option varies a lot, which implies that the electricity price uncertainty has a strong impact on the benefit and should not be neglected in the benefit assessment.

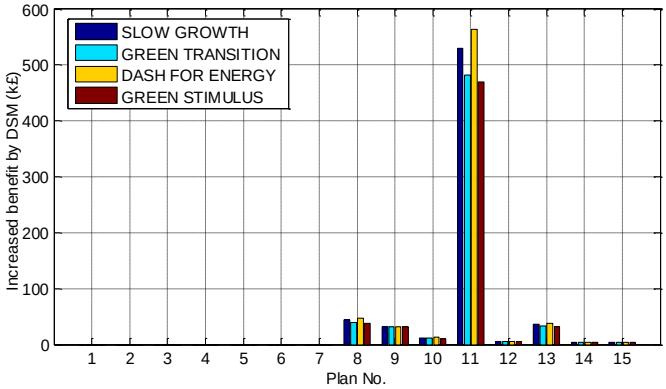

Fig. 9. Increased benefit from DSM

VI. CONCLUSION

This paper applies DSM to ANM to relieve network pressure caused by increasing DG connection in distribution networks. The DSM strategy is achieved through intelligent EV charging, which is realized determined based on network power flow condition in time sequence and limited by time-window scale. A practical 33kV network is exemplified as test system for ANM with DSM to assess the costs/benefits over one year. It is found that with intelligent EV charging, ANM can further reduce generation curtailment, i.e. more renewable energy could be utilized in the network. Results show that up to 7.9% of generation curtailment could be saved compared with the previous ANM. Moreover, it is also found that larger time-window scales always produce better performance, resulting in more generation curtailment reduction. By analysing four different electricity price strategies, the increased benefits from DSM are found to be strongly dependent on electricity price and its uncertainty, which is thus worth noting in optimal network asset investment. In general, the new ANM with DSM can provide a viable and promising enhancement to previous ANM, particularly for networks with high penetrations of renewable generation.

VII. DISCUSSION

This paper proposes a way to apply DSM on the existing ANM to reduce generation curtailment. The results positively approve that combined management of generation and demand can achieve 7.9% improvement in utilization of renewable energy, and subsequently increases the network investment profit by £566k.

Paper [12] shows that the scheme has the potential to increase the capacity of generation connected by upwards of three times the FG connection capacity (i.e. from a FG capacity of 26MW to a total connected capacity of 74MW upwards). Paper [4] indicates that power curtailment proved to have a significant impact on connecting larger volumes of DG, a 5% limit of energy curtailment increases by 30% the wind power capacity. Paper [14] shows the reduction in the level of generation curtailment using AuRA-NMS in term of different additional DG capacity. The generation curtailment reduction can reach 79.6% when the new DG capacity is set to be 40MW. But this paper does not investigate the role that DSM can play in reducing generation curtailment.

It should be noted that the methods devised in this paper and reference are for different objectives with various constraints, and testified on different systems. It is impossible to set a benchmark to measure the benefits they can produce. The work here is improvement over the existing ANM to consider the impact from EV charging. The results in this paper demonstrate that the new method can achieve fairly high benefits on top of the existing work [14].

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