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Enhanced Electric Vehicle Integration in the UK Low-Voltage Networks With Distributed Phase Shifting Control

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ABSTRACT Electric vehicles (EV) have gained global attention due to increasing oil prices and rising concerns about transportation-related urban air pollution and climate change. While mass adoption of EVs has several economic and environmental benefits, large-scale deployment of EVs on the low-voltage (LV) urban distribution networks will also result in technical challenges. This paper proposes a simple and easy to implement single-phase EV charging coordination strategy with three-phase network supply, in which chargers connect EVs to the less loaded phase of their feeder at the beginning of the charging process. Hence, network unbalance is mitigated and, as a result, EV hosting capacity is increased. A new concept, called Maximum EV Hosting Capacity (HC_{max}) of low voltage distribution networks, is introduced to objectively assess and quantify the enhancement that the proposed phase-shifting strategy could bring to distribution networks. The resulting performance improvement has been demonstrated over three real UK residential networks through a comprehensive Monte Carlo simulation study using Matlab and OpenDSS tools. With the same EV penetration level, the under-voltage probability was reduced in the first network from 100% to 54% and in the second network from 100% to 48%. Furthermore, percentage voltage unbalance factors in the networks were successfully restored to their original values before any EV connection.

INDEX TERMS Charging management, electric vehicles, low voltage networks, voltage unbalance.

I. INTRODUCTION

During the past few years, there has been a gradually increasing momentum towards the adoption of low emission vehicles (LEV) including electric vehicles (EV) which is set to increase further in the years ahead. The main drivers are the technological improvement in batteries energy density, government policies and price incentives offered for EV adoption. There are over 40 different EV models available in the UK, more than 90,000 registered EVs on UK roads, and a growing public charging infrastructure with more than 4,000 locations. It is expected that in the next few years more EV models will be launched in the UK by all major car and van manufacturers [1].

However, increased penetration of EVs on the low voltage (LV) distribution networks has negative impacts. These include substation transformers overloading, thermal stress on the lines, voltage drops, voltage unbalance, power losses and rising peak demand [2]–[4].

Many approaches have been proposed to enhance the integration of EVs avoiding network reinforcement which include network reconfiguration [5]–[7], on-load tap changers on secondary substations' transformers, switched shunt capacitors and energy storage [8]–[10], and yet, since uncertainties on EV parameters (location, charge starting time and state of charge) have huge effects on the performance of these algorithms, controlled charging (control over timing, location, and duration of charging) is widely accepted as the facilitator for EV integration [11].

In [12], a trial was performed on nine LV networks in the UK using a centralized control algorithm to manage EV charging points. The control approach used very little information from the network, but an extensive monitoring was still required. EV charging coordination based on

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optimization techniques has been proposed in [13] and [14]. The available power is shared among EVs as much as the network will allow, taking electricity markets bids and prices into account. But again, these techniques rely on extensive network's state information and data processing.

In [15], three EV demonstration projects from US, Germany and Denmark respectively have been analyzed and compared. These projects proposed different technologies for a centralized architecture with an aggregator controlling the charging patterns. The approaches differ conceptually in the way data from EVs are gathered by chargers and in the arrangements regarding the tariffs from the aggregator and charging options to cope with end-user requirements.

For an effective implementation of all the techniques mentioned above, LV networks need to be highly automated. Therefore, the requirements in terms of infrastructure and data processing for these solutions make their adoption in the mid and short-terms unfeasible.

This paper proposes a simple and easy to implement distributed charging control strategy. It is able to mitigate network unbalance due to the single-phase nature of most loads in LV networks which is amplified with the additional and relatively large EV loads. In the proposed single-phase EV charging coordination strategy with three-phase network supply, the chargers connect EVs to the less loaded phase of their feeder at the beginning of the charging process. Hence, network unbalance is reduced and, as a result, EV hosting capacity is increased.

Unbalance between phases in LV networks result in voltage appearing on the neutral connection (zero sequence voltage V_0), and produce phase voltages different in magnitude and no longer phase-shifted by 120°. This affects the performance and life expectancy of the network assets. Phase balancing reduces active power losses and increases the capacity of distribution lines. Methods to balance the network include network reconfiguration, loads control and phase swapping [16]–[18]. But, these techniques require high computational effort for solving the power flow. The complex control systems required, make these strategies unaffordable on today's Distribution Networks (DN).

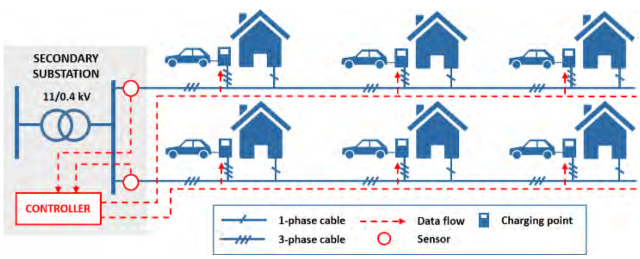

FIGURE 1. **Proposed control architecture for EV charging based on phase-shifting.**

The approach proposed in this paper is similar to that adopted in [18], but with the smart charger only requiring the knowledge of the less loaded phase in the feeder. This information can be easily provided by the secondary substation. The necessary communication between chargers and the controller on the top of the feeder might flow through the existing channel used by smart meters. The suggested architecture is shown in Fig. 1.

The remaining of the paper is organized as follows: Section II describes the methodology of the EV charging strategy proposed in this work. A new concept, called Maximum EV Hosting Capacity (HC_{max}) of LV networks, is introduced to objectively assess the enhancement the proposed strategy could produce. Section III presents a comprehensive assessment of the distribution networks used in this study without any EV integration. Section IV presents a detailed probabilistic analysis of their EV hosting capacities. Section V demonstrates the enhancement achieved with the distributed control algorithm on three real UK LV networks. Section VI discusses the proposed control scheme and conclusions drawn from this work are summarized in Section VII.

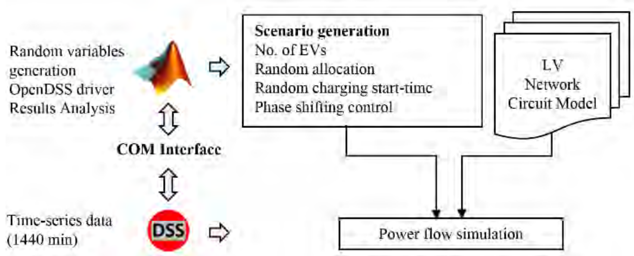

FIGURE 2. **Network simulation methodology.**

II. NETWORK SIMULATION METHODOLODY

To assess the performance of the proposed EV charging control strategy, a series of simulations are presented using Matlab and OpenDSS (an open-source electric power distribution system simulator [19]). Fig. 2 depicts the simulation platform adopted in this work. The LV networks are modeled in OpenDSS and Matlab implements all control algorithms. Communication between the two programs is established via a COM Interface.

The models of three real UK North West's electricity distribution networks (Networks 3, 7 and 21) [20] have been simulated under different hosting scenarios. These models include transformers, lines and load details. The characteristics of these LV networks models including the number of customers, phase distribution, length and geographical layout are summarized in Table 1 and Fig. 3.

Load demand was modeled using a pool of 100 datasets (loadshapes) with 1-minute resolution over 24 hours (1,440 values) based on the CREST tool developed by Loughborough University, UK [21]. This tool provides electricity consumption for a number of typical UK households taking into account the number of residents, month of the year, type of day and the power consumption of major appliances. A typical weekday in January (maximum demand in the UK) was considered with a share of houses having one resident (30%), two residents (34%), three residents (16%) and four residents or more (20%) based on UK National

TABLE 1. Characteristics of LV networks models used.

				Network 3				
	F1	F2	F3	F4	F5	F6		Total
#Customers	94	68	100	38	21	49		370
Phase A (%)	40.4	42.6	32.0	34.2	42.9	40.8		38.1
Phase B (%)	26.6	26.5	31.0	26.3	23.8	32.7		28.4
Phase C (%)	33.0	30.9	37.0	39.5	33.3	26.5		33.5
Length (km)	3.029	2.142	2.312	0.993	0.669	1.338		10.484
Farthest load (m)	448	423	640	619	398	272		640
				Network 7				
	F1	F2	F3	F4	F5	F6	F7	Total
#Customers	71	58	50	186	61	23	22	471
Phase A (%)	42.3	25.9	30.0	31.7	32.8	30.4	40.9	32.9
Phase B (%)	18.3	25.9	30.0	48.9	18.0	56.5	22.7	34.6
Phase C (%)	39.4	48.3	40.0	19.4	49.2	13.1	36.4	32.5
Length (km)	1.716	1.423	1.107	4.197	1.065	0.410	0.559	10.476
Farthest load (m)	501	328	274	465	250	133	239	501
				Network 21				
	F1	F2	F3	F4	F5			Total
#Customers	22	23	67	18	27			157
Phase A (%)	50.0	43.5	34.3	44.4	33.3			38.9
Phase B (%)	27.3	34.8	28.4	27.8	37.0			30.6
Phase C (%)	22.7	21.7	37.3	27.8	29.6			30.6
Length (km)	0.777	0.648	1.226	0.394	1.352			4.396
Farthest load (m)	310	196	211	126	493			493

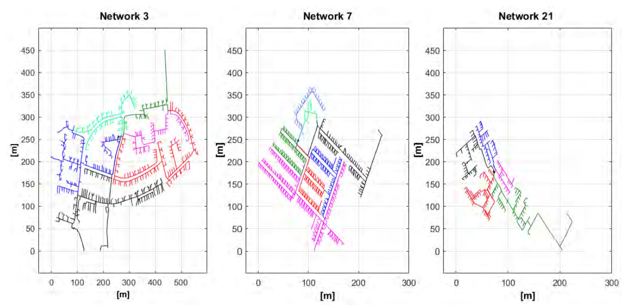

FIGURE 3. Networks geographical layout.

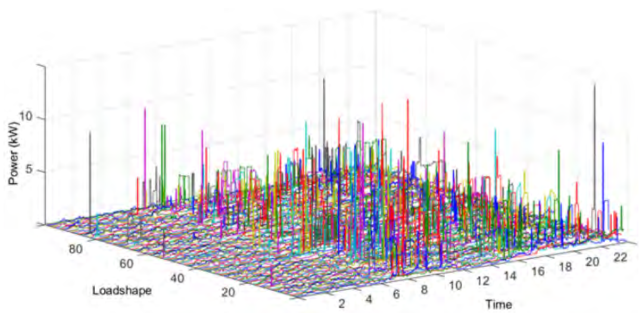

FIGURE 4. Loadshapes pool used in the model.

Statistics [22]. The resulting loadshapes are displayed in Fig. 4. Loadshapes were randomly assigned from this pool to every load in the three networks.

Initially, the performance of the networks without any EV connected was analyzed including powers, transformers saturation, losses, voltage profiles, voltage drops and voltage unbalance along the feeders. Then, the maximum EV hosting capacity (HC_{max}) without control was assessed for each network. This is a new concept introduced in this paper, as EV enhancement resulting from integration techniques has not been quantified before. This is probably due to the random behavior of EV demand with respect to allocation, charging starting time, its duration and power, which makes the quantification uncertain and complex. A probabilistic approach is therefore more appropriate.

In [23], the hosting capacity of a given network is calculated for different charging strategies. The authors defined EV hosting capacity as ''the highest EV penetration rate that can be achieved without exceeding the feeder current constraints and the grid voltage constraints''. This approach used a profile generation technique to statistically represent the household consumption and the EVs charging profiles. Then, based on these profiles, the resulting hosting capacities for the most widely adopted charging strategies such as uncoordinated charging, residential off-peak charging, and EV-based peak shaving were assessed. These penetration rates do not characterize the network hosting capacities as only one scenario regarding household consumption and EVs schedule was considered.

In [11], the DN's EV hosting capacity was defined as the EV charging demand that can be accommodated by the DN such that all the technical constraints (e.g. voltage deviation) are guaranteed and the charging requests of EV owners are fully satisfied. However, the authors did not provide any information on how this could be quantified.

In this paper, HC_{max} is defined as the number of EVs that will cause under-voltages at some charging points of certain feeders with 100% probability. Only slow charging mode was considered in this simulation study with a constant charging rate of 3.6 kW and a power factor of 0.98 lagging.

The proposed algorithm to quantify HC_{max} starts with inputting the number of EVs (N) to be charged. Allocation and charge starting time of each EV are assigned randomly through Monte Carlo simulation by considering only one EV per household. The phase to which each EV is going to be connected to charge will be the phase already feeding the dwelling. The charge starting time is also randomly assigned, between 6 pm and 11 pm and more than one EV can be connected to charge simultaneously. Differences in EVs batteries states of charge (SoC) have not been taken into account, therefore once a vehicle starts charging it will not be interrupted and will continue for 6 hours and 40 minutes to fully charge the 24 kWh battery.

The approach used to estimate the hosting capacity is probabilistic, as it is highly dependent on both EV allocation and charge starting time. To deal with this, the process is repeated 100 times for every number of EVs to be hosted, resulting in the probability of these undesired effects such as under-voltages to occur with that level of EV integration. The number of EVs to be hosted is successively increased by one till this probability reaches 100%. A simplified flowchart of this algorithm is illustrated in Fig. 5.

The EV integration analysis is repeated again, but this time with the application of distributed phase shifting control. Each EV is connected to the less loaded phase of the feeder at the time it starts charging, no matter which phase feeds

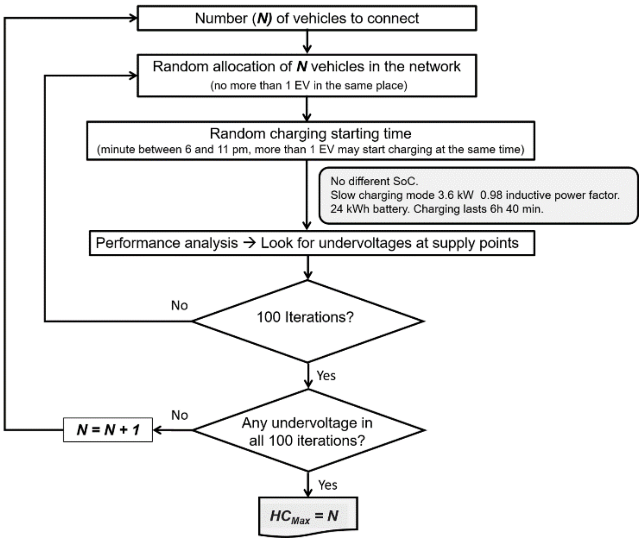

FIGURE 5. Maximum EV hosting capacity of the network *(HC_{max})* assess algorithm.

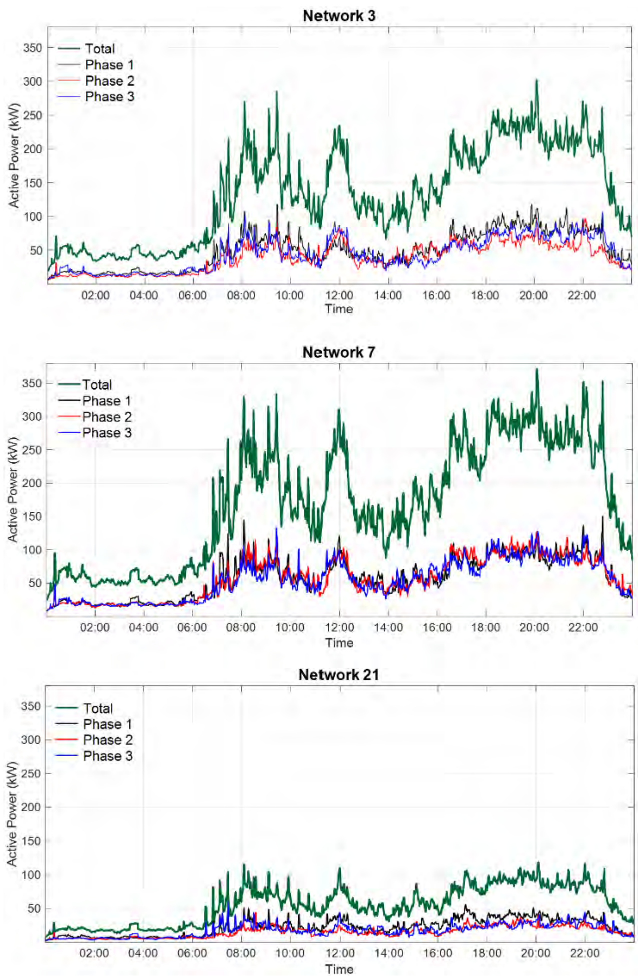

FIGURE 6. Powers delivered by transformers without any EV.

the household. The new HC_{max} values are calculated and the results are compared to quantify the improvements achieved with this control strategy. This process was applied on the three networks and the results are presented in Section V.

TABLE 2. Energy, losses and maximum power along feeders without EV.

	Network 3			
	Supplied energy		Losses	Max power
	(kWh)	(kVArh)	(kWh)	(kW)
F1	792	261	9	72
F2	599	197	6	62
F3	853	281	11	76
F4	329	108	3	38
F5	166	55	1	22
F6	447	147	2	51
Total	3186	1049	32	302
	Network 7			
	Supplied energy		Losses	Max power
	(kWh)	(kVArh)	(kWh)	(kW)
F1	620	202	12	63
F2	500	164	5	48
F3	447	147	3	49
F4	1,605	529	46	141
F5	539	177	4	58
F6	175	58	1	22
F7	205	67	1	27
Total	4091	1344	72	372
	Network 21			
	Supplied energy		Losses	Max power
	(kWh)	(kVArh)	(kWh)	(kW)
F1	171	56	1	24
F2	181	59	0	28
F3	552	181	2	50
F4	169	56	0	21
F5	250	82	1	31
Total	1323	434	4	119

TABLE 3. Saturation and losses of transformers without EV.

	Transformer saturation (%)	Max Power rate	Daily active energy losses (kWh)	Daily reactive energy losses (kVArh)
Network 3	37.75	302/800	3	8
Network 7	46.50	372/800	5	13
Network 21	14.87	119/800	1	1

III. NETWORKS PERFORMANCE WITHOUT EV

Fig. 6 shows the total active power and the active power of each phase delivered by the transformers on Networks 3, 7 and 21 during a whole day.

All the loads are modelled as constant *P* and *Q* with the same power factor of 0.95. Table 2 shows the supplied energy, power losses and maximum power along the feeders of each network during one single day.

Table 3 presents the results related to transformers saturation and losses on each network.

The voltage profiles along the networks without EVs at peak and off-peak hours are shown in Fig. 7. The following color code is adopted in this figure and throughout the paper: Phase 1 (black), Phase 2 (red), Phase 3 (blue). In Network 3, Phase 2 is the least loaded and at peak hour there are points on Phase 1 where the voltage drops close to 0.98 pu. In Network 7, Phase 2 is the most loaded and at peak hour there are points where the voltage reached 0.94 pu. Network 21 is the shortest and less loaded network. The voltage exceeds 1 pu even at peak hour.

The voltage at the load points varies every minute. Fig. 8 shows the range of voltage variation and its average

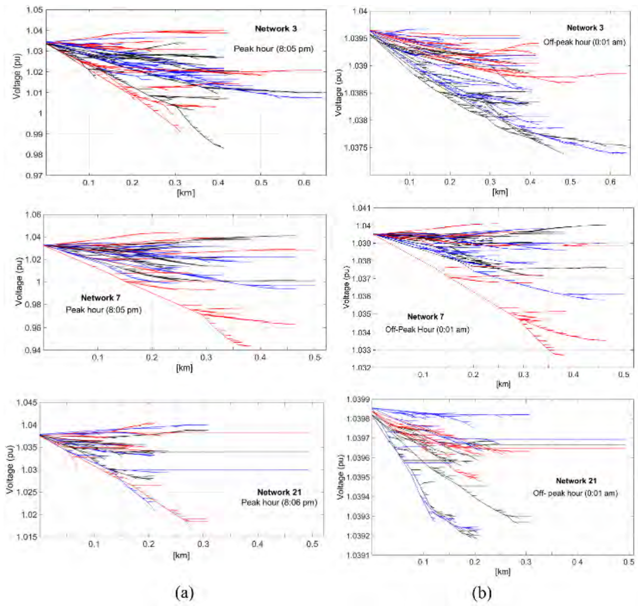

FIGURE 7. Voltage profiles at (a) peak and at (b) off-peak hours without any EV.

value at every supply point. The supply voltage should not differ from the nominal voltage of the system by more than $\pm$ 10% [24], and the results show that this constraint is satisfied. However, in Network 3, feeders 1 to 3 are the feeders with the lowest voltage on Phase 1. This is observed mainly on feeder 2 where unbalance in Phase 1 can be noticed. In Network 7, feeder 4 (the longest with 4,197 m) exhibits a larger unbalance and voltage drops on Phase 2. Network 21 is shorter and has less loads and therefore it does not present any problems in hosting EVs.

The voltage unbalance along the networks was analyzed using the percentage voltage unbalance factor (%VUF), defined as the ratio of the negative sequence voltage component (V^-) to the positive sequence voltage component (V^+) [25].

$$VUF\ (\%) = \frac{V^-}{V^+} \times 100 \tag{1}$$

Distribution Network Operators (DNO) in the UK are obliged to comply with 2% limit of voltage unbalance and 1.3% at the point of common coupling for systems with a nominal voltage below 33 kV [26].

As load demand varies every minute, unbalance varies too. Fig. 9 shows the percentage voltage unbalance factor averages and ranges along the feeders. The maximum %VUF is 1.222% for Network 3, 2.284% for Network 7 and 0.358% for Network 21. They are produced at peak time on feeders 2, 4 and 1 respectively.

IV. EV INTEGRATION ANALYSIS

The next step is concerned with assessing the maximum EV hosting capacity of the networks without any control. The flowchart of Fig. 5 is used to calculate HC_{max},.

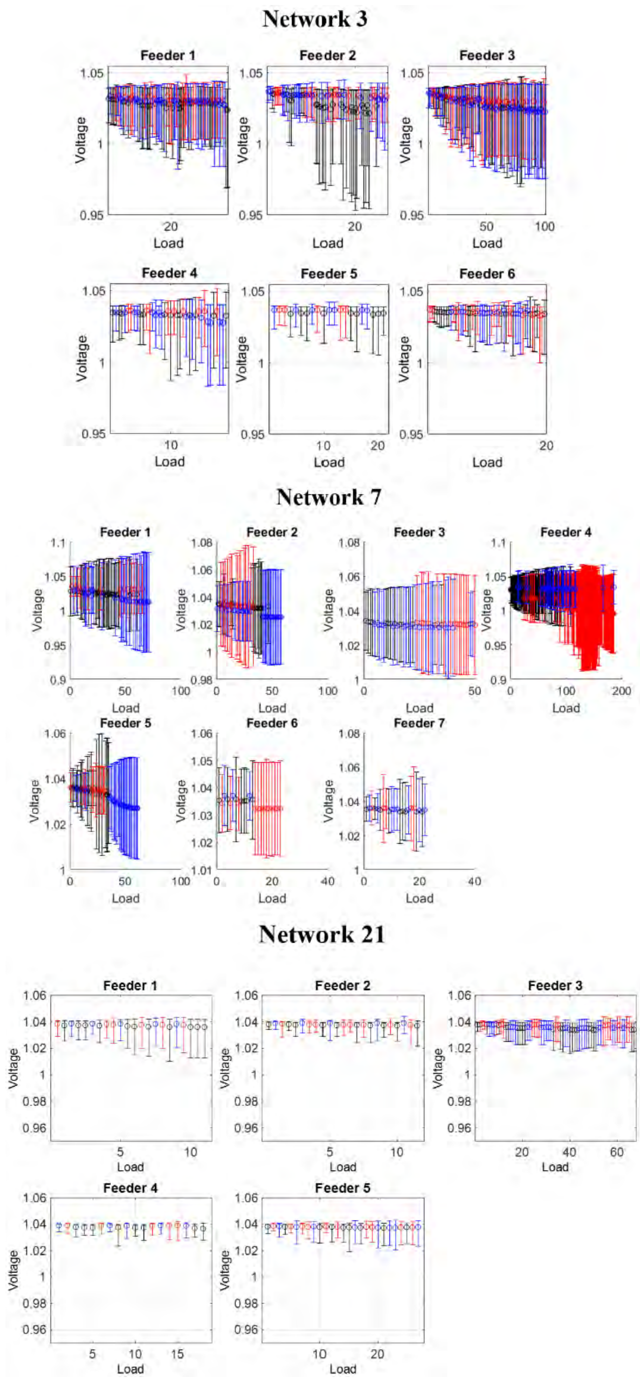

FIGURE 8. Average voltages and ranges at load points without any EV.

The simulations carried out on Network 3 resulted in 100% of under-voltage ($<$ 0.9 pu) probability on at least one supply point, with an EV integration level greater than 56%, i.e. 207 vehicles. For Network 7, HC_{max} was 23%, i.e. 108 EVs. Finally, for Network 21, with the assumption that there is only one EV per house, the expected HC_{max} was not reached. The simulations carried out over this network did not result in any undesirable issues regarding neither voltages nor transformers saturation even with full EV integration, i.e. 157 EVs connected to charge. Table 4 gives the calculated HC_{max} for the three networks.

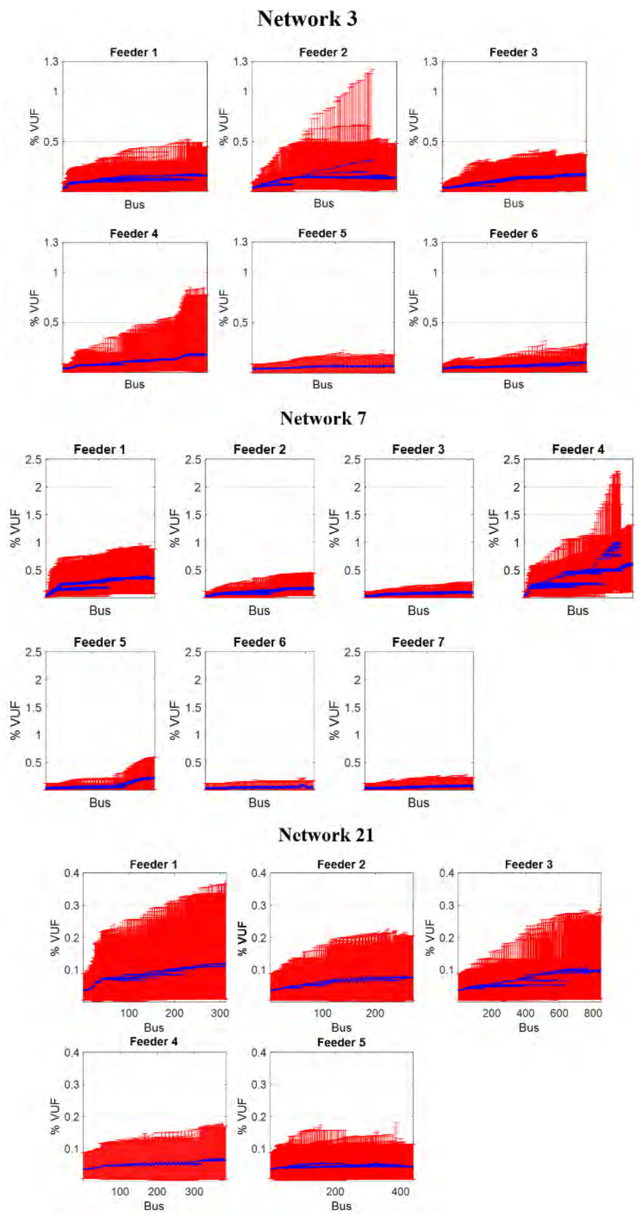

FIGURE 9. Average percentage voltage unbalance factors (%*VUF*) and ranges along the feeders without any EV.

TABLE 4. Under-voltage probability related to EV integration level.

Network 3		Network 7		Network 21	
No. EV (% IL)	uV(P)	No. EV (% IL)	uV(P)	No. EV (% IL)	uV(P)
128 (34.6%)	40%	60 (12.7%)	94%	157 (100%)	0%
135 (36.5%)	50%	70 (14.9%)	96%		
165 (44.6%)	70%	80 (17.0%)	96%		
197 (53.2%)	98%	85 (18.0%)	98%		
199 (53.8%)	97%	90 (19.1%)	99%		
201 (54.3%)	99%	100 (21.2%)	99%		
203 (54.8%)	99%	105 (22.3%)	99%		
205 (55.4%)	99%	107 (22.7%)	99%		
207 (55.9%)	100%	108 (22.9%)	100%		

IL = integration level, uV(P) = under-voltage probability.

When 100% under-voltage probability was reached, the maximum power delivered by the transformer in Network 3 was in the range of 991.9 – 1,019.7 kW in the 100 simulations performed with an average value of 1,007.1 kW (125.88% transformer saturation). The resulting minimum voltage at the supply points was in the range of 0.8385 - 0.8978 pu. For Network 7, the power supplied by the transformer was between 724.8 and 742.9.7 kW with an average value of 735.6 kW (91.95% saturation). The minimum voltage was between 0.8038 and 0.8888 pu. For Network 21, the transformer output power was between 647.9 and 678.9 kW and with an average of 665.9 kW (83.24% saturation). The minimum voltage ranged between 0.9626 and 0.9751 pu. The only difference in these 100% EV integration simulation scenarios on this network, was the EVs charge starting time as every house was allocated only one EV. Table 5 shows the distribution of EVs along the feeders for these scenarios on Networks 3 and 7.

TABLE 5. EV distribution along the feeders.

Network 3			
Feeder	#Customers	No. of EV	
		Case V_{min}=0.8385	Case V_{min}=0.8978
1	94	43	51
2	68	44	31
3	100	39	45
4	38	27	29
5	21	20	20
6	49	34	31
Total	370	207	207
Network 7			
Feeder	#Customers	No. of EV	
		Case V_{min}=0.8038	Case V_{min}=0.8888
1	71	18	21
2	58	10	16
3	50	12	8
4	186	39	33
5	61	14	19
6	23	7	7
7	22	8	4
Total	471	108	108

Fig. 10 shows the power delivered by the transformers on each network with the EV integration level determined by HC_{max} obtained in one of the 100 simulations (100% EV integration for network 21 case). Between 5:40 am and 6:00 pm, the profiles correspond exactly with those shown in Fig. 6 with a different scale. The changes appeared outside that period, when some EVs were charging and unbalance between phases becomes noticeable.

Fig. 11 shows the resulting voltage ranges and averages at supply points during the day obtained from the same simulations. For Network 3, under-voltages appeared on feeders 1 and 3. In other simulation results not, shown here, and with this number of EVs, under-voltages also appeared on feeder 2. For Network 7, the feeders affected by under-voltages were feeders 1 and 4. These two feeders are the longest in the network and have the largest number of connected EVs. For Network 21, there were no voltage deviations but on feeder 3, a 1% gap between average voltages in Phase 2 and others was observed.

The comparison between the percentage voltage unbalance factors along the feeders before (Fig. 9) and after the EV

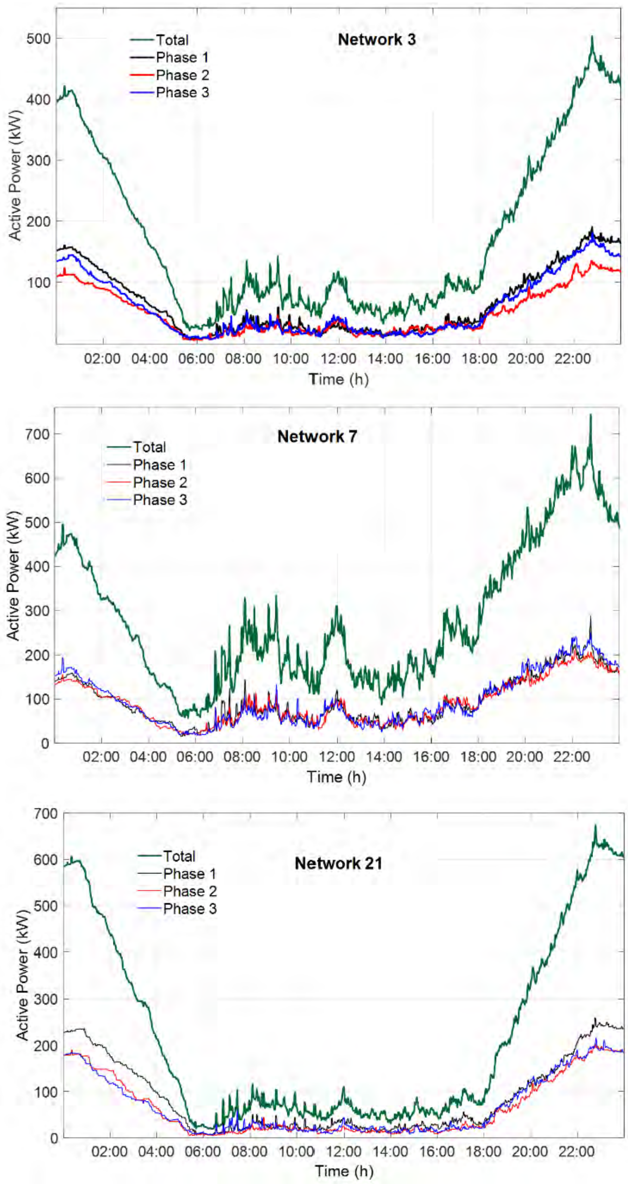

FIGURE 10. Power delivered by transformers with the EV integration level based on the maximum EV hosting capacity of the network (HC_{max}).

integration (Fig. 12), resulted in a considerable rise in $\%VUF$ on all feeders. For Network 3, there was a significant rise of $\%VUF$ to 1.720% on feeder 1. For Network 7, $\%VUF$ increased to 3.517% on feeder 4 and in Network 21, feeder 1 showed an increase in $\%VUF$ about three times the unbalance obtained previously without EVs.

V. ENHANCED EV INTEGRATION WITH DISTRIBUTED PHASE SHIFTING CONTROL

The method proposed to enhance EV integration is based on identifying the less loaded phase at the top of the feeder every time a new EV is being connected to the network, and then shifting the connection if this causes an overload on the phase. In other words, instead of connecting the EV to the phase supplying the dwelling, it will be connected to the less loaded phase of that feeder at that time.

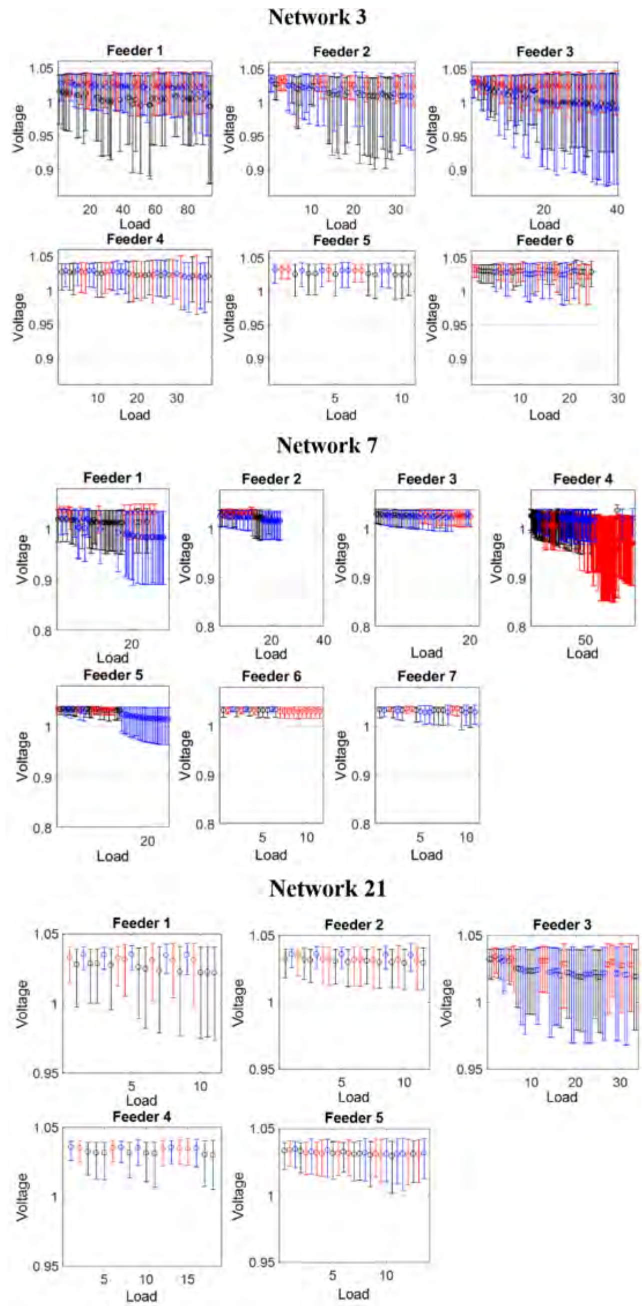

FIGURE 11. Average voltages and voltage ranges at the supply points with the EV integration level based on the maximum EV hosting capacity of the network (HC_{max}).

This control strategy was implemented on the three networks. Firstly, the under-voltage probability was assessed with the same EV integration level defined by the HC_{max} of the network. Secondly, the new HC_{max} was evaluated with the proposed control. Furthermore, to deal with any possible random scenarios, the probability-based approach consisted of 100 different simulations for every level of integration, with a random assignment of locations and charge starting times for every EV.

The HC_{max} for Network 3 without any coordination was 55.9% (207 EVs for which under-voltages will appear at

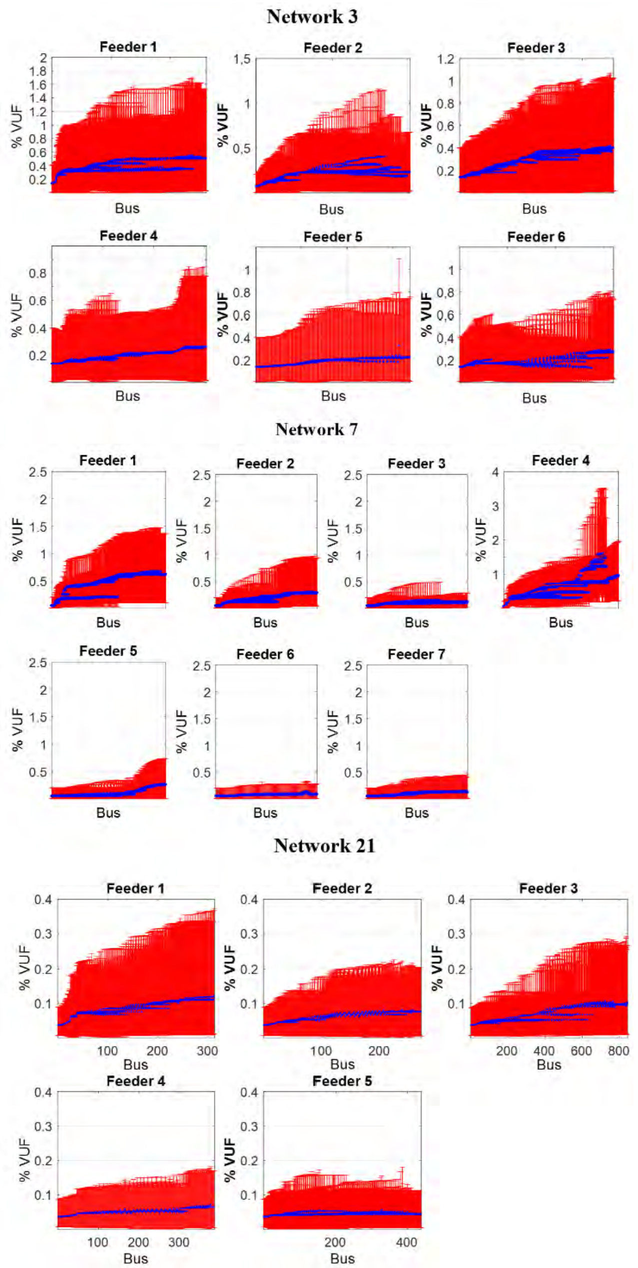

FIGURE 12. Percentage voltage unbalance factor *(%VUF)*, averages and ranges with the EV integration level based on the maximum EV hosting capacity of the network *(HC_{max})*.

some supply point of some feeder with 100% probability). With phase-shifting control, the under-voltage probability with 207 EVs was reduced to 54%. For Network 7, with 108 EVs the under-voltage probability dropped to 48%. In Network 21, there were no under-voltages observed neither with nor without control.

Table 6 presents the number of supply points with under-voltage (*SPU*) probability with the number of EVs given by HC_{max} without control. For Network 3, there were 46 scenarios with no under-voltage issues. In the worst-case scenario, 45 out of 370 (12.16%) supply points exhibited under-voltage. In Network 7, the worst-case scenario

TABLE 6. Number of supply points with under-voltage probability.

Network 3 (207 EV, 370 supply points)		Network 7 (108 EV, 471 supply points)	
SPU	Probability	SPU	Probability
0	46%	0	52%
1-10	4%	1-10	8%
11-20	8%	11-20	5%
21-30	20%	21-30	5%
31-40	15%	31-40	3%
41-50	7%	41-50	7%
51-60	0%	51-60	10%
61-70	0%	61-70	5%
71-80	0%	71-80	3%
81-90	0%	81-90	2%
> 90	0%	> 90	0%

SPU= supply points with under-voltage probability.

TABLE 7. EV distribution along the feeders for extreme SPU results.

Network 3			
Feeder	#Customers	No. of EV SPU = 0	No. of EV SPU = 45
1	94	56	42
2	68	43	33
3	100	42	64
4	38	27	25
5	21	15	14
6	49	24	29
Total	370	207	207
Network 7			
Feeder	#Customers	No. of EV SPU = 0	No. of EV SPU = 82
1	71	16	16
2	58	14	10
3	50	10	8
4	186	41	51
5	61	11	9
6	23	7	8
7	22	9	6
Total	471	108	108

SPU= supply points with under-voltage probability.

was 82 out of 471 (17.41%) supply points exhibited under-voltage at some time during the day.

Table 7 shows the distribution of EVs along the feeders that produced the two extreme *SPU* results. Feeders 3 and 6 in Network 3 and feeders 4 and 6 in Network 7 are the feeders with the largest number of EVs and those which affected the grid the most by producing 45 and 82 supply points with under-voltage respectively.

Fig. 13 shows the power delivered by the transformers with the EV integration level determined by the HC_{max} of the networks (100% for Network 21), obtained in one of the 100 simulations (case $SPU = 0$) with phase shifting control. A comparison with the results of Fig. 10 shows that, in this case, there is a balance between phases during EV charging period.

The average voltages and ranges at supply points resulting from the same simulations ($SPU = 0$) are shown in Fig. 14. These results clearly demonstrate the benefits and improvements achieved with the proposed control strategy.

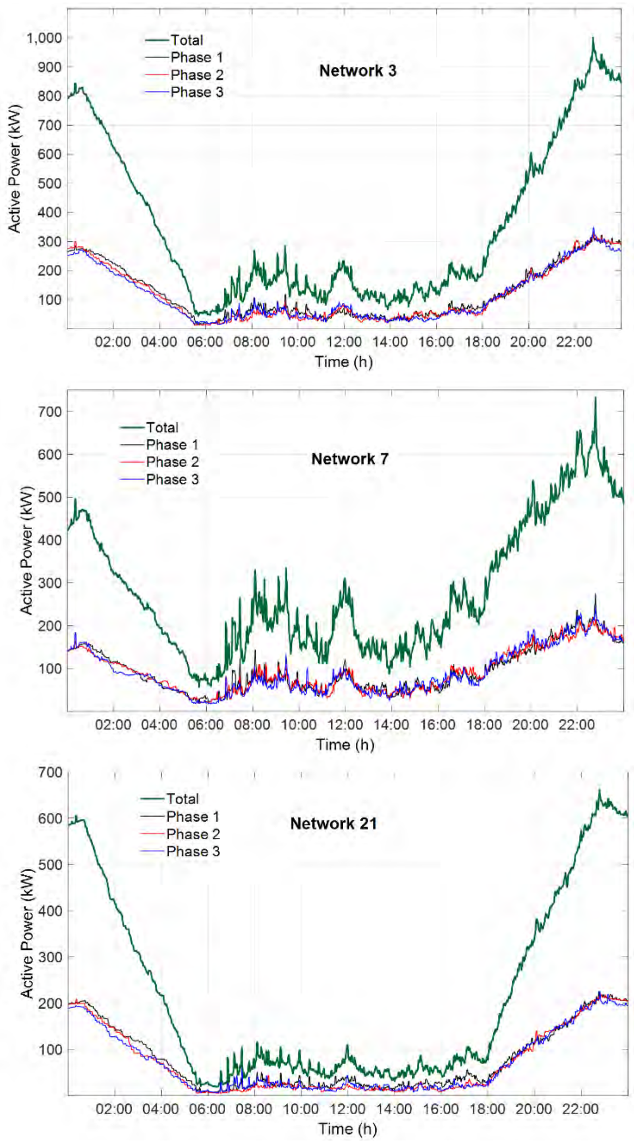

FIGURE 13. Power delivered by transformers with the EV integration level determined by the maximum EV hosting capacity of the network (HC_{max}) with phase shifting control.

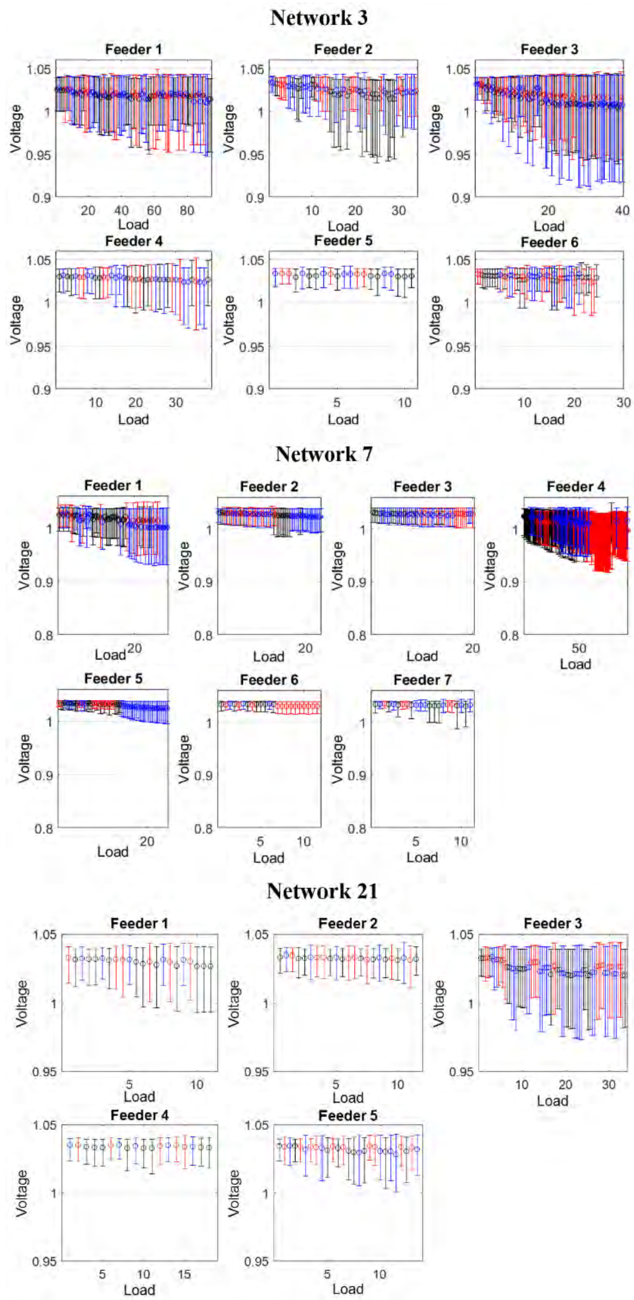

FIGURE 14. Average voltages and voltage ranges at supply with the EV integration level determined by the maximum EV hosting capacity of the network (HC_{max}) with phase shifting control.

There are no under-voltages, higher minimum values and a better balance between phases.

The $\%VUF$ averages and ranges along the feeders that resulted from the same simulations ($SPU = 0$) are shown in Fig. 15. A comparison with Fig. 12 (without control) reveals a substantial improvement in the performance of the networks. In Network 3, without EVs the maximum $\%VUF$ was 1.222%, with EVs and uncontrolled charging 1.720% and with EVs and distributed control 1.447%. In Network 7 without EV the maximum $\%VUF$ was 2.284%, with EVs and uncontrolled charging 3.517% and with EV and distributed control 2.292%. Finally, in Network 21 without EVs the maximum $\%VUF$ was 0.258%, with EVs and uncontrolled charging 0.774% and with EVs and distributed control 0.361%.

The unbalance occurring outside the charging periods may not be improved by the proposed control. For this reason, the maximum $\%VUF$ during a day with EVs and controller will be equal to the existing $\%VUF$ without EVs or greater.

Finally, for Network 3 it was necessary to increase the number of EVs to 274 to get a 100% under-voltage probability. With phase-shifting control, the EV hosting capacity HC_{max} increased from 54% to 74%. For Network 7, HC_{max} increased from 23% to 46% (218 EVs) with the proposed distributed control scheme.

In [11], the EV penetration level (EV_p) was defined as the ratio of total EV charging demand to the total DN demand

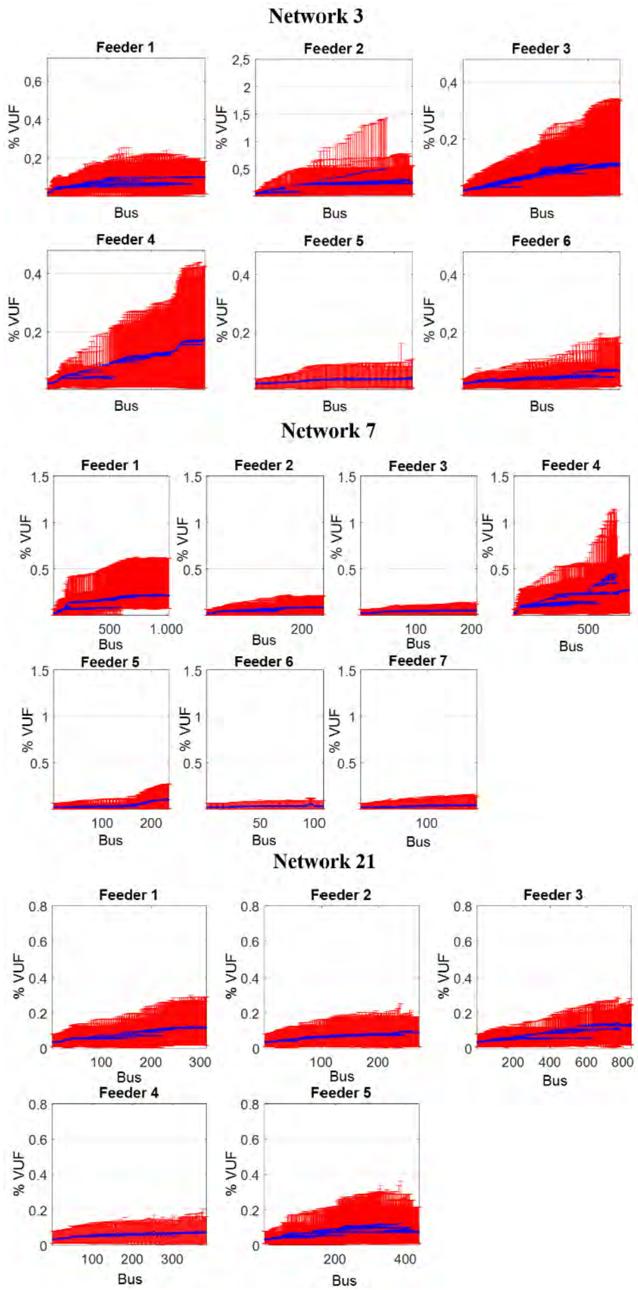

FIGURE 15. Percentage voltage unbalance factor *(%VUF)* averages and ranges along the feeders with phase shifting control.

during the day, with the following formulation.

$$EV_p = \frac{\sum_{t\epsilon T}\sum_{c\epsilon C} P_{c,t}^{CH,AV}}{\sum_{t\epsilon T}\sum_{j\epsilon J} p_{j,t} + \sum_{t\epsilon T}\sum_{c\epsilon C} P_{c,t}^{CH,AV}} \tag{2}$$

where $p_{j,t}$ is the active power at node j at time t, $P_{c,t}^{CH,AV}$ is the average aggregated EV charging demand at time t and at charging facility c, C is the set of EV charging facilities, T is the set of time slots and J is the set of DN nodes. Note that, with this definition the resulting EV_p is the same and does not depend neither on the charging time (since it was assumed that $SoC = 0$ and charging duration = 6 h 40 min) nor on the allocation. It varies only with the number of EVs.

For Network 3, with 207 EVs, the EV penetration level was $EV_p = 0.6093$. For Network 7, with 108 EVs, $EV_p = 0.3878$. Finally, for Network 21 with 157 EVs, $EV_p = 0.7401$. With the same EV penetration level, with the distributed control, the under-voltage probability was reduced in Network 3 from 100% to 54% and in Network 7 from 100% to 48%. However, Network 21 with the higher penetration level did not show any problem. The EV penetration level is not a valid indicator of the hosting capacity.

VI. DISCUSSION

To successfully implement the control scheme presented in this paper, the following elements are required: a controller in the secondary substation, chargers with phase-shifting ability and a communication channel between chargers and the controller.

The controller has a very simple function: gather and compare phase powers from each feeder and transmit a code pointing to the less loaded phase. These tasks can easily be performed by many intelligent electronic devices (IED) or programmable logic controllers (PLC) which are available in the market.

Chargers will receive the information about the phase that should feed the next EV which is going to be connected if any. The phase shifting strategy can be implemented using static transfer switches based on triacs like in [18]. Note that there will not be any stability issues since no dynamic load switching is pretended and the phase-shifting would take place before charging starts.

Since charging may be temporarily interrupted without affecting the customer comfort, EVs can be considered as shiftable loads. A remote control over the EV single-phase charger with direct three-phase connection to the LV network, would provide distribution network operators (DNO) with direct load control and would allow EVs to participate in demand side management programs.

Concerning the communication requirements, there is already, in many countries including the UK, a communication infrastructure in place that could be used to implement this control system. This is the smart metering network. There are over 4.2 million smart meters operating across homes and businesses in the UK, deployed by both large and small energy suppliers. The UK Government through the Smart Metering Programme aims to roll-out smart meters to all domestic properties in the UK by the end of 2020. This means that there will be a communication channel between every consumer and the DNO. This communication channel is already bidirectional, as it allows remotely switching the supply on and off. In fact, one of the common minimal functional requirements for smart meters described in [27] is to provide two-way communication between the smart metering system and external networks for maintenance and control.

When compared to more advanced control charging techniques, the proposed chargers do not need to supply any information to the aggregators. Hence, EVs do not require any communication protocols and are therefore easily adapted to the control system. The communication infrastructure already exists and the automation is simple and easy to implement. Only three phase network supply is required. In addition, advanced application of this distributed phase shifting control architecture would enable DNO to manage demand response and balance networks, improving the benefits of advanced smart meters for demand response based control of distribution networks [28].

Phase-shifting is not a new idea and has been applied to reduce voltage unbalances in power systems. However, this concept, to the best of the authors' knowledge has not been applied to EV charging management.

VII. CONCLUSION

In this paper, a simple and effective single-phase EV charging coordination strategy with three-phase network supply has been proposed. Chargers connect EVs to the less loaded phase of their feeder at the instant when charging begins. With this control strategy, the network unbalance is mitigated, the performance of the network is enhanced and hence the EV hosting capacity is increased.

The improvements achieved with this control scheme have been demonstrated on three real UK residential networks with different configurations. As EV hosting capacity is highly dependent on location, charge starting time and state of charge, a comprehensive Monte Carlo simulation study using Matlab and OpenDSS tools has been performed.

To objectively quantify the hosting capacity enhancements that phase-shifting control could bring to distribution networks, a new concept called Maximum EV Hosting Capacity (HC_{max}) of low voltage distribution networks, is introduced. It is defined as the number of EVs for which, under-voltages will appear at some service point of a feeder (100% probability) and its assessment is probabilistic.

The HC_{max} of the three networks were calculated without phase-shifting control (207 EVs 56%, 108 EVs 23% and 157 EVs 100%) and with phase-shifting control (274 EVs 74%, 218 EVs 46% and 157 EVs 100%). With the same EV penetration level, the under-voltage probability was reduced from 100% to 54% in the first network and from 100% to 48% in the second network. The third network did not present any under-voltages neither without nor with charging control. However its unbalance was improved.

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