IEC 61851 COMPLIANT DEMAND SIDE MANAGEMENT ALGORITHM FOR ELECTRIC VEHICLE CHARGING: A MILP BASED DECENTRALIZED APPROACH

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Abstract

Charging scheduling algorithms play a vital role in diminishing the negative consequences on electricity networks from the widespread adaptation of electro-mobility. Therefore, there is a growing interest in a pragmatic solution that requires only modest resources. To reach this goal, we propose a decentralized, IEC charging standard compliant, two-layer charging scheduling algorithm, which only requires unidirectional communication and reduced computing capabilities. The objective of the algorithm proposed is to achieve valley filling by exploiting the flexibility of electric vehicles through optimal tracking of a target signal. The IEC standard compliant, semi-continuous charging characteristic is attained with a mixed-integer linear formulation. Different formulations of the problem by forming vehicle groups and randomization in charging events are examined. The results show that the IEC 61851-compliant formulation with a semi-continuous charging characteristic for the proposed method fails to perform as good as the variable charging rate formulation, which has a 2.8 and 3.9-fold deviation in the variance of the total demand relative to the variable charging rate at 50% and 100% penetration rates, respectively. Nevertheless, the inclusion of randomization and grouping improves the performance of the IEC standard-compliant formulation. Considering four groups, the variance in demand of semi-continuous charging formulation at 50% penetration is nearly equal to that of the variable charging rate proofing the viable potential of the technically feasible solution proposed.

1 Introduction

The increasing trend towards electrification of the transportation sector has raised a series of technical problems affecting the healthy operation of the electricity network. A number of studies have already highlighted such negative consequences [1–4]. To reduce the impacts of the widespread integration of electro-mobility on the distribution grids, control strategies for electric vehicle (EV) charging are crucial.

A wide range of such demand side management strategies, which exploit the temporal flexibility of the EVs, are discussed in the literature demonstrating a strong potential [5–10]. These studies employ distinct control architectures and methodologies for the charging scheduling process. The majority of the charging schemes proposed employ a variable charge rate, considering that the EV can withdraw power at any rate between zero and a given maximum rate. However, the IEC 61851 standard specifies that beyond the standby mode, the charging current has to be in the range from 6 A to 48 A, being then a semi-continuous variable [11]. Therefore, the studies with variable charge rates, do not meet compliance with the standard IEC 61851. Due to the limitations of the charging technology, the economic and practical deployment of the proposed strategies are therefore debatable.

In a previous study, we proposed an autonomous decentralized demand side management (ADSM) algorithm for EV charging scheduling to flatten the aggregated demand at the low voltage (LV) distribution transformer [12]. The proposed control architecture can be easily deployed by means of a simple embedded controller attached to the EV supply equipment (EVSE) owing to the linear formulation of the optimization. The method also only relies on unidirectional communication and therefore requires few communication resources. These features render it well suited for practical implementations. Similar to the works in [5–9], a variable charging rate, which is not in accordance with IEC charging standards, was assumed, in our previous implementation [12]. Hence in this paper, we aim to adapt this control architecture to comply with charging limits specified in the standards. To meet the requirement defined in the standards, a semi-continuous charging rate is used, which is either zero or varies between the minimum and maximum values. The semi-continuous charging characteristic is realized using a mixed integer linear programming (MILP) formulation.

The aim of the study proposed is to provide an exemplary case that demonstrates the impacts of compliance with standards in control algorithms of EV charging upon the intended outcomes and establish a simple, practically viable control algorithm for EV charging scheduling.

The rest of the paper is arranged as follows. A detailed description of the MILP formulation for the decentralized ADSM method proposed is presented in Section 2. Section 3 includes the simulation setup that we used for the analysis. The simulation results are presented in Section 4 followed by a conclusion in Section 5.

2 Method

The decentralized hierarchical ADSM approach proposed in our previous study is referred to as Optimal Power Tracking (OPT) [12], since the fundamental principle is to track a predefined reference power signal with minimal deviations. The tracking signal is determined to achieve valley filling by exploiting the flexibility of EV demand. The algorithm is formulated in a two-layer architecture as presented in Figure 1. In the first layer, the DSO determines a target power signal S based on the estimates of non-elastic power demand D^* and aggregated total EV demand E^* and broadcasts to all the EVs. In the second layer, with the knowledge of EV user behaviour estimates (arrival times $t_{j,\text{arri}}$, departure times $t_{j,\text{dep}}$, energy demand E_j^*), each EVSE scales the received signal to the expected day ahead EV energy demand and performs an optimization to track the scaled signal with minimal deviations.

2.1 Determination of the target signal

The tracking signal is determined based on the estimated day ahead aggregated non-EV demand profile (D^*) and the estimated total EV energy demand of all the grid-connected EVs (E^*). The day-ahead prediction of the non-elastic load profile is realizable through forecasting tools, in particular, AI-based techniques that are capable of learning complex nonlinear relationships from the historic data [13]. The recent developments in substations equipped with intelligent transformers facilitate the measured load demands [14]. Sub-metering systems offer the possibility to measure the historical EV demand data which can be used to decouple the EV demand to obtain the non-elastic demand. The estimation of the aggregated EV flexibility in the form of a total energy demand value is also achievable with AI-based techniques [15].

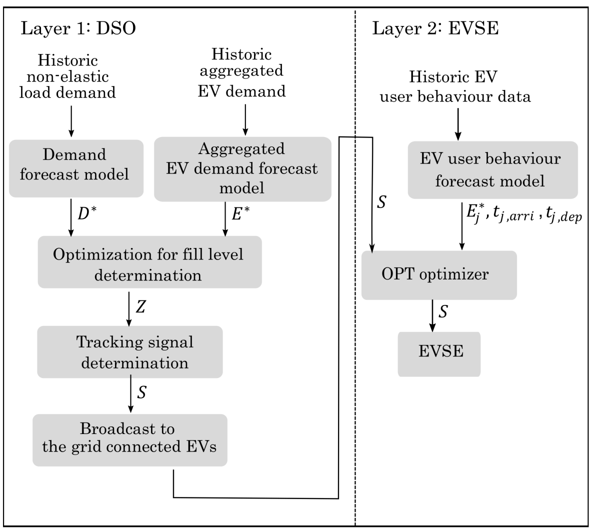

Fig. 1 The two-layer architecture of the optimal power tracking demand side management algorithm for EV charging.

The first step to determine the target signal is to obtain the fill level Z by solving,

$$\sum_{t=1}^{N^{\mathrm{T}}} \max\{(Z - D_t^*), 0\} \, \Delta t = E^*, \tag{1}$$

for Z using the two estimates in accordance with the classical water filling algorithm [16]. N^{T} is the total number of time steps of length Δt in the optimization window. The mismatch between the fill level and the estimated non-elastic load profile at each time interval for the optimization horizon S_t is computed and transmitted to the EVs:

$$S_t = Z - D_t^*. \tag{2}$$

2.2 Local optimization at the EVSE with MILP

In the second layer of the OPT, a local optimization is performed by each EV controller. The local controller attached to the EVSE, splits the negative S_t^- and positive S_t^+ parts of the original power signal received S_t. Thereafter, the tracking signal to be optimally tracked is determined using the estimated next-day EV demand for each EV. The tracking signal for the j^{th} EV,

$$S_{j,t}^+ = \frac{E_j^*}{\sum_{t=1}^{N^T} S_t^+ \, \Delta t} S_t^+ \tag{3}$$

is derived by scaling S_t^+ to the estimated next day energy demand for the j^{th} EV, E_j^*. The optimization problem is devised to track the S_t^+ with minimal deviation given the EV user behaviour predictions. Methods for EV user behaviour predictions based on clustering [17], data-learning [18], data-driven [19], etc. are discussed in the literature. We proposed a linear formulation in [12] to the optimization problem stated, which demands reduced computational cost. However, as already stated above, the previous implementation assumes a variable charging rate. To meet compliance with the limits specified by the IEC 61851 standards, we re-formulated the original, linear optimization in a MILP formulation. The objective and the associated constraints of the optimization problem are listed below, where j refers to the j^{th} EV.

$$\min \sum_{t=1}^{N^{\mathrm{T}}} \left[a_{j,t}(1+S^{-}_{t}) + b_{j,t}\right] \Delta t \qquad \text{s.t.} \tag{4}$$

$$-a_{j,t} \leq S^{+}_{j,t} - P_{j,t} \leq a_{j,t} \qquad \forall t, \forall j, \tag{5}$$

$$-b_{j,t} \leq P_{j,t+1} - P_{j,t} \leq b_{j,t} \qquad \forall t, \forall j, \tag{6}$$

$$SOC_{j,\text{min}} \leq SOC_{j,t} \leq SOC_{j,\text{max}} \qquad \forall t, \forall j, \tag{7}$$

$$x_{j,t}P_{j,\text{min}} \leq P_{j,t} \leq x_{j,t}P_{j,\text{max}} \qquad \forall t, \forall j, \tag{8}$$

$$x_{j,t} \in [0,1] \qquad \forall t, \forall j, \tag{9}$$

$$b_{j,t} \geq 0 \qquad \forall t, \forall j, \tag{10}$$

$$x_{j,t} = 0 \qquad \forall j, \text{for } t, \text{where the EV is not at home.} \tag{11}$$

Here, $a_{j,t}$ and $b_{j,t}$ are two sets of auxiliary variables, $SOC_{j,\text{min}}$ and $SOC_{j,\text{max}}$ are the minimum and maximum permissible state of charge of the battery of EV_j, specified by the manufacturers. The SOC of vehicle j at time step t is derived assuming a linear battery dynamics:

$$SOC_{j,t} = SOC_{j,0} + \frac{1}{C^{\mathrm{B}}_{j}} \Big\{ \sum_{s=1}^{t} \eta_{j,\mathrm{c}}\, P_{j,s}\, \Delta t - \sum_{s=1}^{t} E_{j,s} \Big\} \tag{12}$$

where, $E_{j,t}$ refers to the energy demand for driving. $P_{j,t}$ is the charging power of the EV_j at time t. $P_{j,\text{min}}$ and $P_{j,\text{max}}$ are the minimum and maximum permissible charging power of the battery either defined by the EVSE or EV manufacturer. $x_{j,t}$ is a binary variable, which for each EV at time t specifies charging (1) or not-charging (0). It is used to implement the semi-continuous charging characteristics in compliance with the IEC standards for each EV_j at time t.

2.3 Randomization and grouping

The limits imposed on the minimum charging current can result in new peaks due to simultaneity, especially at high penetrations. To mitigate this drawback, a randomization and a grouping mechanism are used in the decentralized controllers.

A grouping mechanism, implemented by the DSO, randomly assigns each EV to one of the N_g groups. A new target signal for each group $S_{g,t}$ is derived by segmenting the original target signal S_t into N_g signals, each exhibiting the same time integral reflecting energy. A given EV will receive the target signal created for the group and the total number of EVs present in the group ($N_{\text{EV},g}$). Subsequently, the EVs perform the MILP optimization described in the previous section alongside a randomization process.

In the randomization process, each controller generates a random probability for every time slot of the target signal using a uniform distribution. Only if the probability is higher than a threshold value, charging is allowed. The threshold probability $P_{\mathrm{T},t}$ at time step t is determined based on the percentage of EVs in the group able to charge simultaneously at the minimum charge rate without exceeding the target signal:

$$P_{\mathrm{T},t} = 1 - \Big(\frac{S^{+}_{g,t}}{P_{\text{min}} N_{\text{EV},g}}\Big) \tag{13}$$

The performance of the method is highly dependent on the number of groups. Hence, we evaluate and compare the results for different numbers of groups.

3 Simulation Setup

In our study, we conducted load flow simulations of a distribution grid to assess different performance indicators. The load flow simulation [20] implemented in MATLAB® [21] uses the backward forward sweep flow method [22] which is equally applicable for both radial and weakly meshed grids as proposed by Ghatak and Mukherjee. The OPT linear optimization problem is solved using the MATLAB® implementation of cutting plane and branch and bound algorithms. We conducted simulations over a week with a time resolution of 15 minutes. The selected week was chosen from the winter season as it exhibits a higher demand compared to other seasons. The optimization problem is solved every 24 hours at noon, taking into account the forecasts for the next 36 hours. We consider overlapping time windows for the optimization to ensure that the SOC of the vehicle is always within the limits, guaranteeing the energy required for driving is delivered without failure. The simulations are performed under the assumption of perfect predictions of the uncertain parameters since the scope of the study is to evaluate the feasibility of the proposed concept.

3.1 Grid simulation model

The topological data of a LV grid in Austria was used as the test grid in this study. The data used to model the grid including information on the distribution transformer, loads (location, load type, annual energy consumption), and topology (connectivity, cable type, length) were provided by the local DSO, Vorarlberger Energienetze GmbH [23]. The simulated LV distribution grid comprises a 800 kVA, $10/0.42$ kV step-down, 3-phase transformer with 52 load nodes and 103 distribution lines. The grid supplies 490 residential consumers, 9 business units, and 77 other consumer units including heat pumps, public facilities, etc. Data related to the annual energy consumption for each consumer was also made available by the local DSO. The grid simulation was conducted considering the LV side of the transformer as the slack node with a reference voltage of 1 p.u.

3.2 Household load demand

For the non-elastic household demand data, the Irish Commission for Energy Regulation (CER) dataset from a smart metering project was used [24]. These data having a half-hour sampling time were re-sampled to a sampling interval of 15 minutes. After filtering the incomplete data, a data set of 4225 customers was considered. The household demand data spans over a year from 14th July, 2009 to 31st December, 2010.

3.3 EV load demand data

The historical residential charging data were obtained from records of the experimental statistics of the Electric Charging Point Analysis project funded by the Office of Low Emission Vehicles [25]. The records include charging events spanning over a year for residential charge points in the UK. The data contains time-stamp data that determines the corresponding time of connection (start time of charging session), the time of the disconnection (end time of charging session), the amount of energy supplied, and the charging rate for each identified charging session. To demonstrate the feasibility of the concept, a perfect prediction of EV usage behaviour was assumed.

3.4 EV specifications

In modeling the electric vehicle, we used the specifications of the Nissan Leaf with a battery capacity of $C_j^{\mathrm{B}} = 40$ kWh. We assume that the charging infrastructure is equipped with a 3-phase 400 V/16 A semi-fast charger with a maximum charging power of 11 kW having a charging efficiency of $\eta_{j,\mathrm{c}} = 0.9$.

3.5 Simulation scenarios

The simulations were performed for a range of EV penetrations (0% - 100%, in steps of 10%). We defined EV penetration as the percentage of households that own an EV. The benchmark case with no EVs is included in the analysis for the purpose of reference, which is referred to as the 0% penetration case. We also simulated the uncontrolled EV charging scenario (Unc), where the EVs start charging as soon as they arrive at the point of charging, at a maximum charging rate until fully charged. The results for the proposed MILP-based scenarios are compared with our previously proposed setting with a variable charge rate scenario (hereafter referred to as VC). Different formulations of the proposed MILP solution to the OPT approach were considered to achieve comparable optimality to the VC scenario. The outcomes of the straight transformation of the OPT approach into MILP are denoted as SC. As discussed in Section 2, the MILP formulation of OPT with randomized charging events without group formulation is represented by the scenario SC_1. The MILP formulation with randomization and grouping from two to six groups is represented by the scenarios SC_2-SC_6.

4 Results

This section provides a comparative analysis of the performance of the MILP formulations of OPT for EV charging management presented in Section 3.5 using several performance indicators. The intended objective of the OPT algorithm is to fill the valleys of the non-elastic demand curve utilizing EV demand flexibility by tracking a pre-defined reference signal. Valley filling is primarily employed to reduce the variance in the demand profile. Therefore, we used the variance in total demand as an index to measure the performance of the different formulations proposed which is shown in Figure 2 for the penetration range considered. For the purpose of comparison, the variance normalized to the variance of the 0% penetration is used.

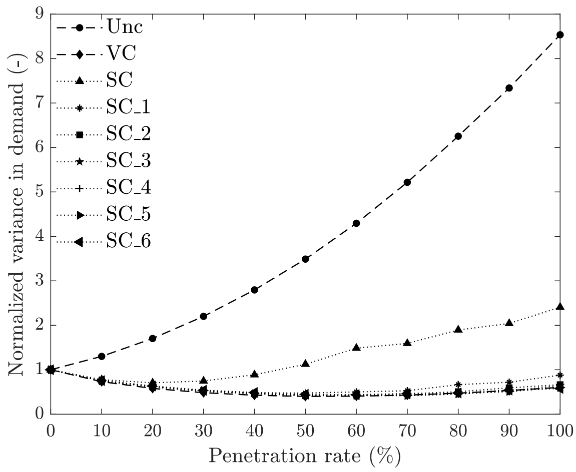

Fig. 2 Variance in the total demand normalized to the variance of the 0% penetration for uncontrolled, OPT with variable charge rate (VC), OPT with semi-continuous charge rate (SC), OPT with semi-continuous charge rate and randomization in charging (SC_1), OPT with semi-continuous charge rate and randomized charging with two to six groups (SC_2-SC_6).

The formulation of OPT with semi-continuous (SC) charging alone reduces the variance in comparison to uncontrolled EV charging, but shows a significant deviation from OPT with VC, which is more noticeable at high penetrations as observed in Figure 2. This can be attributed to the concurrent charging of a high number of EVs at the minimum permissible charging rate during the deep valley periods. The randomization process improves performance to a high extent across all penetrations, whilst still exhibiting a slight variation at high penetration. The inclusion of grouping leads to a performance much closer to the implementation of OPT with VC. Increasing the number of groups results in better performance, however, a group number of four is adequate to achieve similar performance to OPT with VC up to a penetration of 50%.

The valley-filling nature of OPT also aids in reducing the peak-to-average power ratio (PAPR) of the networks. A comparison of the PAPR is shown in Figure 3.

Similar to the results presented in Figure 2, the PAPR of the OPT algorithm with SC charging is on an equitable level to that of OPT with VC only at low penetrations, in our specific configuration up to a penetration of 30%. The SC charging with randomization shows comparable results up to a penetration of 70%. The adoption of grouping further improves the PAPR results. The results also demonstrate that at high penetrations, a high number of groups leads to more favorable results in PAPR.

The OPT method has several other advantages besides valley filling and peak reduction capabilities. We have demonstrated in [12] that the OPT approach positively influences the voltage violations in the nodes and current violations of the cables in the LV grids. Therefore, we evaluated the variations between the different OPT formulations on these two parameters. A

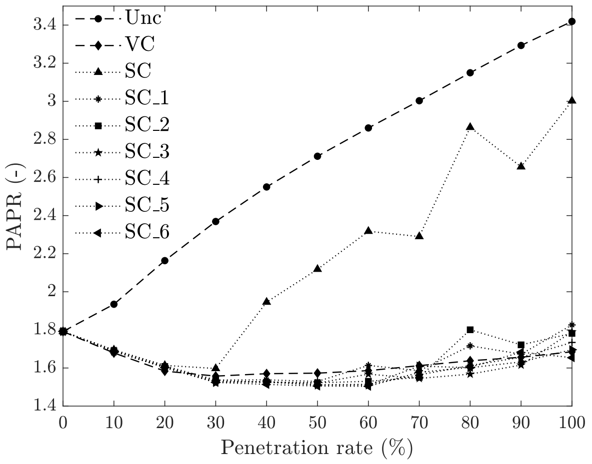

Fig. 3 Peak to average power ratio (PAPR) for uncontrolled (Unc), OPT with variable charge rate (VC), OPT with semi-continuous charge rate (SC), OPT with semi-continuous charge rate and randomized charging (SC_1), OPT with semi-continuous charge rate and randomized charging with two to six groups (SC_2-SC_6).

comparison of voltage deviations for the penetration ranges considered is presented in Figure 4. In summary, the influence of the different MILP formulations on the voltage deviations follows a similar trend to that of the variance and PAPR indices.

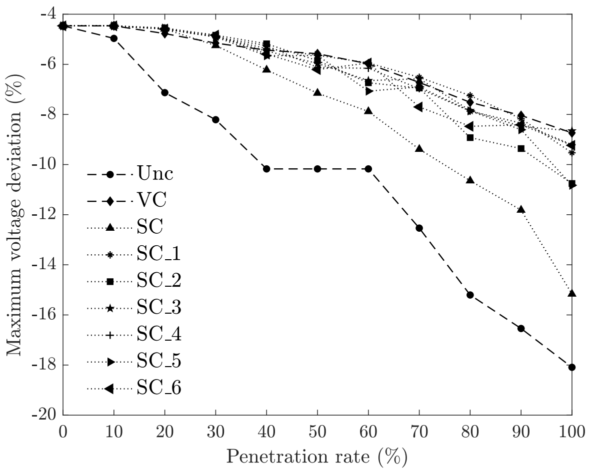

Fig. 4 Maximum voltage deviations in the grid nodes for uncontrolled (Unc), OPT with variable charge rate (VC), OPT with semi-continuous charge rate (SC), OPT with semi-continuous charge rate and randomized charging (SC_1), OPT with semi-continuous charge rate and randomized charging with two to six groups (SC_2-SC_6).

Further, we examined compliance with the voltage standard criteria defined in EN 50160. The selected LV network exhibited a resilient behaviour in terms of voltage. The compliance with EN 50160 was found to be violated at a penetration of 70% at uncontrolled charging of EVs. All OPT formulations with randomized charging provided successful mitigation to these voltage violations.

An overview of the number of events where the cables exceed the permissible currents in the simulated week is shown in Table 1. The number of cables exceeding the limit is denoted in the brackets.

Table 1 Summary of cable overloading events (number of cables affected) within the simulated week

Penetration (%)	Unc	VC	SC	SC_1	SC_2	SC_3	SC_4	SC_5	SC_6
10	2 (2)								
20	40 (2)								
30	111 (6)								
40	203 (8)	4 (2)	6 (4)	4 (2)	4 (2)	4 (2)	4 (2)	4 (2)	4 (2)
50	273 (11)	12 (4)	26 (5)	20 (4)	18 (4)	14 (4)	14 (4)	14 (4)	12 (4)
60	381 (11)	28 (4)	79 (6)	44 (4)	40 (4)	42 (4)	42 (4)	38 (4)	32 (4)
70	527 (12)	66 (4)	256 (10)	102 (4)	102 (4)	96 (4)	88 (4)	86 (4)	72 (4)
80	688 (16)	120 (4)	402 (13)	157 (5)	152 (4)	160 (4)	138 (4)	134 (4)	132 (4)
90	833 (20)	167 (7)	568 (16)	221 (7)	212 (7)	200 (7)	206 (7)	191 (7)	188 (7)
100	981 (25)	203 (7)	632 (18)	261 (9)	260 (8)	259 (7)	255 (7)	234 (7)	235 (7)

In the selected grid, cable overloading problems start to occur already at low EV penetration rates, i.e., at 10%. The OPT with VC mitigates the cable overloading problems up to a penetration of 30% while reducing the overloading problems at penetrations beyond that. The SC formulations with grouping realize comparable results to that of the VC formulation. The SC formulation having random load scheduling and a grouping of six shows the closest performance to the OPT implementation with VC rate in reducing the overloading events.

In summary, the findings demonstrate that the MILP formulation to the OPT algorithm to achieve semi-continuous charging characteristics as defined by the IEC standards, does not perform as well as OPT formulation with the variable charge rate. The introduction of randomization and grouping improves performance, whereby an increasing number of groupings contributes positively.

5 Conclusion

We present a decentralized charging scheduling algorithm that is practically feasible, requires less communication and computational cost, and complies with IEC 61851 charging standard. The primary objective of the algorithm is valley filling, achieved by optimally tracking a target power signal exploiting the flexibility of EVs. The method exhibited promising results when used in a previous implementation with a variable charging rate which is not in compliance with the IEC standards.

In this study, the proposed method is extended to ensure compliance with the IEC standards. A mixed-integer linear optimization formulation was adopted to realize the semi-continuous charging characteristic to meet compliance with the IEC standards. The results show that the MILP formulation fails to perform successfully compared to the variable charging rate implementation, indicating a 2.8 and 3.9-fold deviation in the variance in demand at 50% and 100% penetration rates.

To overcome this limitation, the method is extended with a modification involving a randomization and grouping mechanism. The randomization process alone improves the performance of the variance in demand, being 1.2 and 1.5-fold with respect to the variable charge rate at 50% and 100% penetration rates, respectively. The adoption of the grouping enhances the performance further, in particular for high penetrations. The best performance was achieved with six groups; the highest number of groups we employed, with a variance in demand of 1.04 times that of the variable charge rate, at 100% penetration rate, indicating the proposed method to be a feasible implementation.

The performance of the proposed method subjected to the various uncertainties associated will be considered in a future implementation. The incentives for consumer participation and the policy framework for the implementation in practice remain to be developed by the DSO.

6 Acknowledgements

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7 References

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