Online Distributed Voltage Control of an Offshore MTdc Network using Reinforcement Learning

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***Abstract*—This paper addresses one of the main challenges on the way to an offshore transnational multi-terminal dc (MTdc) network: its control and operation. The main objective is to demonstrate the feasibility of using reinforcement learning (RL) techniques to control, in real time, a multi-terminal dc network aimed at integrating offshore wind farms (OWFs). This method of controlling MTdc networks using RL techniques is called Online Distributed Voltage Control (ODVC). The ODVC strategy uses Continuous Action Reinforcement Learning Automata (CARLA) to optimize power flows in real time. To validate the effectiveness of the proposed control method, dynamic simulations are carried out using a MTdc grid model composed of six nodes, interconnecting three offshore wind farms to three European countries. The results obtained demonstrate the advantages of implementing an online distributed voltage control strategy to obtain feasible controlled power flows with low transmission losses. The results obtained demonstrate the feasibility of the proposed method to control, in real time, MTdc networks and that the RL techniques are well-suited for this problem due to their inherent advantages of coping with stochastic environments.**

Nomenclature

CARLA	Continuous Action Reinforcement Learning Automata
CDF	Cumulative Density Function
HVac	High-Voltage ac
HVdc	High-Voltage dc
MTdc	Multi-Terminal dc
ODVC	Online Distributed Voltage Control
OPF	Optimal Power Flow
OWF	Offshore Wind Farm
PI	Proportional Integral
PDF	Probability Distribution Function
RL	Reinforcement Learning
TSO	Transmission System Operator
VMM	Voltage Margin Method

I. Introduction

The current European trend to build offshore wind farms with ever higher installed capacities is expected to continue. Estimations are that by 2020 circa 40 GW of offshore wind power will be installed in Europe, with potential to reach 114 GW by 2030 [1]. Moreover, the distances to shore have, and still are, steadily increasing with the advent of new technologies [2]. Fig. 1 shows the distance to shore, installed capacity and transmission technology for completed, or under construction, offshore wind farms (OWFs) [3], [4].

Given the current trends in offshore wind, the Northern EU countries have plans to build offshore transmission networks due to its advantages and opportunities, such as renewable energy integration [5]; powering oil & gas platforms [6]; interconnecting EU electricity markets [7]–[9] and supporting ac grids via ancillary services [10], [11]. Fig. 1 shows that when the distances were between 10 km and 50 km, and the OWF installed capacity was higher than 100 MW, high-voltage ac (HVac) has been the technology of choice. However, for higher installed capacities and distances greater than approximately 50 km, high-voltage dc (HVdc) is overtaking HVac as the chosen transmission technology. In Europe, Germany already has several offshore wind farms which will be connected to shore through an HVdc transmission line [3].

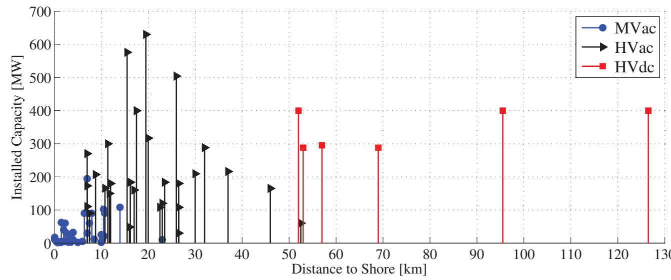


Fig. 1: Distance to shore, transmission technology and installed capacity of offshore wind projects [3].

Due to the increasing number of offshore projects, there are cooperations, such as Coreso and the North Seas Countries' Offshore Grid Initiative, which study the planning, development and operation of a common offshore grid infrastructure [9]. Based on the advantages of HVdc transmission systems, most studies recognize that offshore grids will probably be built as multi-terminal dc (MTdc) networks. However, there are four main challenges to the development of multi-terminal HVdc networks, namely: system integration, protection, dynamic behavior and power flow control [12].

System integration aspects of multi-terminal dc networks have been tackled in [9], [11], [13]. The dynamic behavior of MTdc networks (including multi-level converter topologies) has also been extensively analyzed [14], [15]. On the protection aspects, several studies have focused on how dc fault develops [16], [17], dc fault detection methods [18], [19], research and development of HVdc switch breakers [20], [21] and other protection systems [22]–[24].

Power flow control will be key to the development of MTdc networks, hence, it has been thoroughly analyzed [14], [25]. However, the commonly employed control strategies, such as droop control or the voltage margin method, are not optimized for online operation, i.e.: the possibility to optimally control in real time the power flow in the MTdc network according to the OWFs production and the needs of the transmission system operator (TSO).

Therefore, this work aims on testing the Distributed Voltage Control (DVC) strategy together with a reinforcement learning (RL) technique which optimizes the power flow inside MTdc networks in real time. The DVC strategy is combined with continuous action reinforcement learning automatons (CARLAs) to achieve fast online optimization capability. The CARLAs take into consideration the power production at the OWFs, the dispatch plans of the TSO and the actual state of the system, e.g. regarding faults.

The paper is structured so that it first introduces what is needed to control the power flow in MTdc networks. Afterwards, the DVC strategy is presented and the online optimization tool is explained. Subsequently, the DVC strategy is demonstrated in a case study with three OWFs. Finally, conclusions are drawn on the strategy effectiveness.

II. Control of MTdc Networks with VSC-HVDC

A. Power Flow Control in MTdc Networks

Nearly all HVdc transmission systems worldwide are point-to-point. In these systems, one terminal controls the direct voltage while the other controls the active power through the link. In a MTdc network, to guarantee stability, i.e. power balance between all terminals, the system direct voltage must be well controlled within stiff limits at all times. Therefore, in a MTdc network, the direct voltage control has to be shared between more terminals mainly due to two reasons: firstly, the VSCs have limited power ratings; secondly, faults in the ac network, to which the VSC is connected to, limit its ability to transfer power with the MTdc network [25].

A control strategy for large MTdc networks should have:

- high flexibility: capacity of performing different market dispatch schemes [26];
- fast dynamic behaviour: capability of reliably operating the network during sound and contingency scenarios, e.g. voltage dips or disconnection of an onshore station;
- High expandability: independence from the network topology to allow expansion of the grid or temporary disconnection of cables for maintenance purposes;
- Low communication requirements: capability of performing acceptable operation during communication delays or failure.

Several control strategies which share the direct voltage control amongst more terminals to operate MTdc networks have been proposed in the literature. For example, the Voltage Margin Method (VMM), initially thought for controlling MTdc networks using HVdc classic technology, uses two or more proportional-integral (PI) controllers in a cascade configuration [27]. Although, the task of controlling the direct voltage is shared among multiple stations, only one terminal controls the voltage at a time. In addition, if an outage occurs at the voltage-controlling station, undesired abrupt transitions may occur in the direct voltage inside the network [28]. Another method to control the direct voltage is the voltage droop method which has its simple control structure (proportional gain) as an advantage. Although, this method does not offer a high controllability over the network power flow in its standard form, recent works have been conducted to enhance the method [29]–[35]. Hybrid control strategies aiming to obtain enhanced control schemes, which combine the previous two methods, were already presented in the literature [28], [36], [37]. The studies in [10], [38] presented a comparison between different direct voltage control methods, including the voltage droop method and the VMM.

B. The Distributed Voltage Control Strategy

The power flow in a transmission line of a dc network can be calculated as:

$$g_{P_i} = P_{Gi} - P_{Li} - \sum_{j \neq i} V_{dci} V_{dcj} Y_{ij} - Y_{ii} {V_{dci}}^2 \tag{1}$$

where g_{P_i} is the load flow equation of node i in the MTdc network; P_{Gi} and P_{Li} Are the power generated and load at node i, respectively; V_{dci} is direct voltage of terminal i; and Y_{ij} is the coefficient from the admittance matrix at position ij.

From (1) it becomes clear that the power flow control in a multi-terminal dc network has to be achieved by controlling direct voltages of the system. The DVC strategy assigns each onshore VSC terminal with a specific voltage set-point. In this way, the MTdc network voltage control is distributed amongst the onshore nodes. This control approach increases reliability, by adding redundancy, and provides the possibility to control the power flow inside the dc network to any feasible load flow scenario.

The DVC strategy flowchart is shown in Fig. 2. The method works as follows: at first, the DVC receives the power production at the OWFs. Then, a distributed dc load flow algorithm is run to obtain a first solution for the optimal power flow (OPF) algorithm. The constraints and specific parameters for the OPF can be set by the TSO.

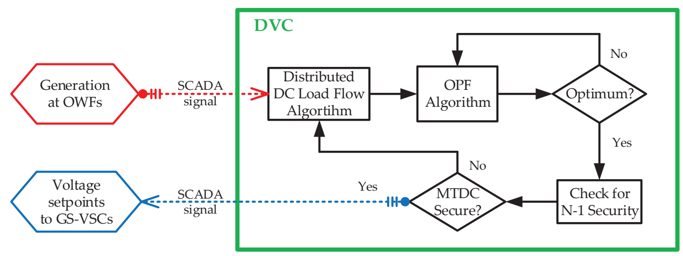


Fig. 2: Flowchart of the DVC strategy.

Next, the solutions generated by the OPF algorithm are checked for N-1 security. The distributed DC load flow algorithm then checks, with one dc node defective at a time, whether the MTdc network is N-1 secure for the obtained power-flow scenario. If there is a feasible solution which is N-1 secure, the DVC sends the direct voltage set-points to VSC-HVdc terminals controlling the MTdc network voltage.

The next section explains the CARLAs used in the DVC strategy.

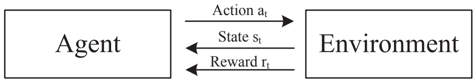
III. The CARLA optimization technique

As the DVC strategy relies on the solution of an OPF problem, any optimization method could in principle be used. However, fast optimization techniques are needed for the DVC to operate a MTdc network in real-time. In this paper the DVC strategy is then combined with a RL technique employed to optimize the DVC strategy for online real-time utilization.

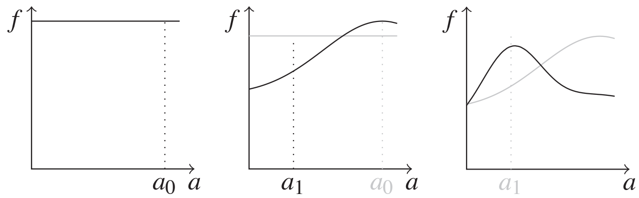
A. Reinforcement Learning

Reinforcement learning focuses on solving complex dynamic problems through a trial-and-error process [39]. RL algorithms solve a problem online, improving performance over time through interaction with the problem itself. A learning agent takes actions to solve an unknown problem where "good" actions are rewarded and "bad" actions are punished. This feedback is encoded in a reward function that is problem specific. Fig. 3(a) shows an abstract agent-problem, or agent-environment, interaction model.

The learning agent observes the system state at time t, s_t. Based on that observation, the agent takes an action, a_t, according to its



(a) The agent-environment interface.



(b) Three CARLA time steps with actions a_0 and a_1 [40]

Fig. 3: Conceptual principles of RL techniques.

current policy, which is a mapping from states to actions. Performing this action has an effect on the environment, and causes it to transition to a new state, s_{t+1}. The agent observes this new environment state and receives a reward, r_t, which evaluates the transition. Based on the feedback, the agent updates the current policy such that, next time when in state s_t, it has a higher probability of taking the action with highest expected reward. Since initially the problem is unknown, the agent must first take random actions and learn their effect onto the environment, which can be done for instance through numeric simulations. As the agent's knowledge increases, better actions are taken.

B. Continuous Action Reinforcement Learning Automaton

CARLA is a model-free RL technique for solving problems with a continuous action domain [40]. Each problem variable is controlled by a CARLA which learns a Probability Distribution Function (PDF) over the variable domain, $A \in [A_{min}, A_{max}]$. The CARLA, which starts with a uniform PDF, samples an action from the PDF and executes it. It then updates the PDF based on the reward received. Fig. 3(b) illustrates these two steps: first, the CARLA samples and executes action a_0; subsequently, it updates the PDF based on the observed reward. Lastly, using the new probability distribution, action a_1 is sampled and executed, and the PDF is updated once again.

Instead of the PDF, the Cumulative Density Function (CDF), F, is stored since the CDF is required for the sampling action and calculating it for a non-parametric PDF is computationally expensive. The CDF at time $t+1$ is constructed as follows:

$$F_{t+1}(a) = \begin{cases} 0 & a < A_{min} \\ \gamma_t \left(F_t(a) + \delta D_t(A_{min}, a_t)\right) & a \in A \\ 1 & a > A_{max} \end{cases} \tag{2}$$

where,

$$\begin{cases} \delta_t = \beta_t(a_t)\alpha\lambda_t\sqrt{2\pi} \\ \gamma_t = \dfrac{1}{1+\delta_t D_t(A_{min}, A_{max})} \\ D_t(x,y) = F_{N(0,1)}(\dfrac{y-a_t}{\lambda_t}) - F_{N(0,1)}(\dfrac{x-a_t}{\lambda_t}) \\ \lambda_t = \lambda_0 \dfrac{12\sigma_t}{(A_{max}-A_{min})^2} \end{cases}$$

The new CDF, F_{t+1}, depends on the previous one, F_t, and the last interaction with the environment, a_t. The learning rate, α , is the strength of a single update, whereas λ_0 is the initial spreading rate, or the breadth of the impact of a single update. Both parameters are set beforehand, with $\alpha = 0.1$ and $\lambda_0 = 0.2$. The reward function to be maximized is given by β, whereas σ_t is the standard deviation of the recently taken actions, and $F_N(0,1)$ is the standardized normal CDF.

When solving a problem with n variables, n CARLAs are required. Each of them samples one variable and the collective problem solution is afterwards tested. The solution effect is measured, and returned to the CARLAs, in the form of a scalar reward. The CARLAs then update their CDFs based on this feedback. In this way, independent CARLAs can collaborate to achieve improved problem solutions.

IV. The DVC Strategy with CARLA optimization

The combination of the DVC strategy with CARLA optimization may be explained by Fig. 4, where the communication flow is shown. Initially, the power production at the offshore wind farms is measured and sent to the DVC at the TSO center, which, knowing the MTdc network topology, solves the OPF problem according to the system constraints using the CARLA optimization in real time. During a control cycle, the CARLAs are iteratively sampling direct voltage values. These sampled values are evaluated and, if they present a better reward value, they are kept in an archive. Finally, at the end of each control cycle, the direct voltage references present in the archive are sent to the onshore stations and the process is repeated[1].

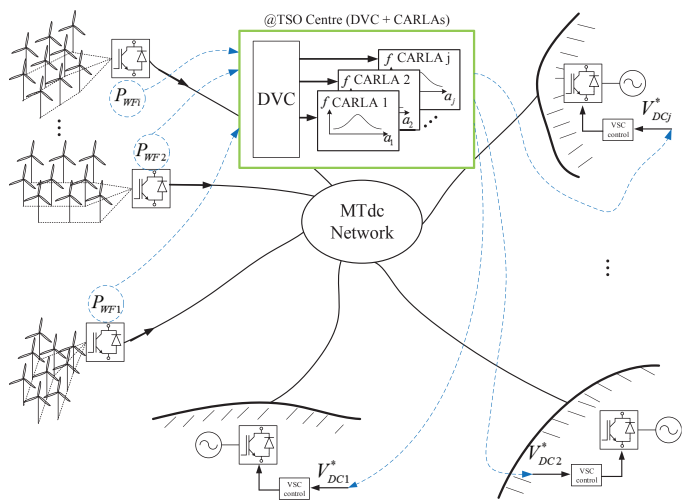


Fig. 4: Information flow between the OWFs, the CARLAs and the onshore VSC stations.

As the problem is dynamically changing every control cycle, due to the wind variability, the CARLAs adapt themselves by shifting their CDFs. This constitutes the main advantage of online learning techniques since a typical offline optimization algorithm will always solve the problem from scratch on every control cycle [41].

The DVC strategy is able to comply with all the requirements needed to control a MTdc network provided that the VSC-HVdc stations can promptly and accurately follow a direct voltage reference [38]. Therefore, the direct voltage control of the onshore VSC-HVdc stations is locally performed by a PI regulator to achieve null steady-state errors. Fig. 5 shows how the local control on each onshore VSC-HVDC is done [10], [42], [43].

[1]A pseudo-code of the procedure is given in the Appendix.

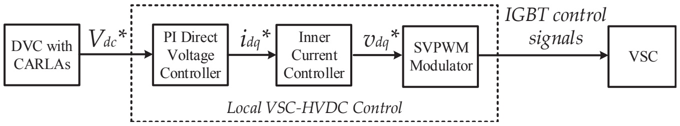


Fig. 5: Control diagram of the onshore VSC-HVdc stations.

A. Optimization Goal

In this work, the optimization goal is to minimize the MTdc network transmission losses, expressed as:

$$P_L = (\mathbf{I_M V})^{\mathbf{T}} \mathbf{Y_P} (\mathbf{I_M V}) \tag{3}$$

where, P_L is the transmission losses, $\mathbf{I_M}$ is the incidence matrix, $\mathbf{V}$ is the direct voltages vector and, and $\mathbf{Y_P}$ is the MTdc network admittance matrix.

B. Variables

The direct voltages of the onshore stations are the optimization variables. Each CARLA is assigned to optimize the voltage of one station as shown in Figure 4. Together, all the voltages, together with the offshore wind power production define the load flow.

C. Constraints

Different constraints are implemented to assure that the direct voltage references obtained by the CARLAs correspond to feasible operating points of the MTdc network:

- VSC stations rated power is respected;
- nodal direct voltages are within steady-state limits;
- current in the dc cables are admissible;
- the network is N-1 secure, i.e. the MTdc network remains operational, with direct voltages within limits, even if an ac outage occurs in any of the VSC terminals [11].

D. Reward Function

The reward function, β, used to update the CARLAs is:

$$\beta = -(P_L(a) + C(a)) \tag{4}$$

where $P_L(a)$ is the transmission losses and $C(a)$ is the sum of the constraint violations.

The reward function is negative as CARLAs are defined as a maximization technique.

E. System States

Different system states may occur during the operation of a MTdc network:

- Normal state: no constrains over the power flow;
- Constrained state: a certain power has to be transferred to an onshore node;
- Contingency state: an ac fault at an onshore station.

The behavior of the onshore nodes is different according to the system state. For instance, if an onshore station suffers an ac fault it cannot transfer power. Therefore, all onshore stations have a CARLA for each MTdc network state. In this way, the next time a particular system state occurs each CARLA is already adapted to it and already biased towards certain solutions (direct voltage reference value).

However, due to the wind variability, when a state has not been active for some time, the CARLAs CDFs may no longer provide optimized power flows. Therefore, whenever the environment changes to a new state, the CDFs of the remaining states are decayed. This decay does not erase the previously acquired knowledge, but encourages more exploration in order to find better solutions. The decay is applied as:

$$F_{t+1}(a) = 0.01 F_t(a) + 0.99 F_U \tag{5}$$

where F_U is the CDF of an uniform distribution.

V. Numeric Simulations

Numeric simulations are carried out first to demonstrate the performance of the DVC strategy with the CARLAs. Details of the simulated MTdc network and the case study results are presented next.

A. Case Study

The MTdc network topology and its transmission cables length are indicated in Fig. 6. The network has six nodes, which interconnect three OWFs to the onshore ac networks of the UK, Germany and Denmark. Each OWF has an installed capacity of 1.2 GW (1 pu). The MTdc rated voltage is $\pm$320 kV, and all the onshore VSCs are connected to ac substations with a short-circuit level of 3600 MVA (3 pu). Table I displays the MTdc network parameters.

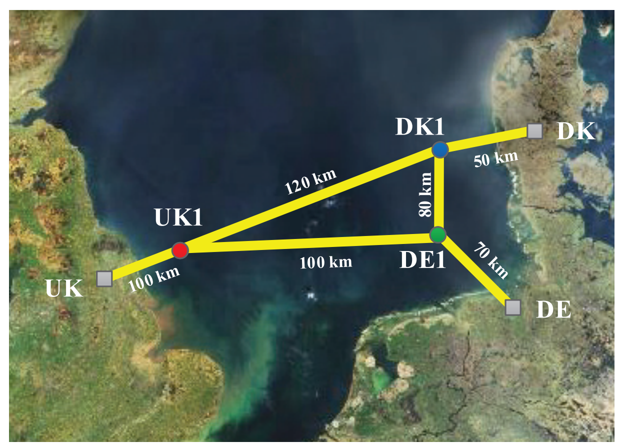


Fig. 6: The 6-node-meshed connected offshore MTdc network used in the simulations.

TABLE I: System Parameters.

	Parameter		Unit	Value
System base	Rated Power	S_b	MVA	1200
DC System Voltage base	Rated Voltage	V_{dc}	kV	$\pm$320
Short-circuit Ratio	SCR	-	pu	3
MTdc Network	Cable impedance	Z_{dc}	Ω/km	0.0126+j0.06
			nF	220
	Cable rated power	P_{dc}	MW	1200

The dynamic models of the ac grids, MTdc network and VSC used in the numeric simulations are explained in detail in [38], [42]. The OWFs are modeled as current sources and real wind data was used to represent the OWFs power production. The measured wind data is from a single wind turbine, hence, it was smoothed to emulate the power production of a complete wind farm [44]. Fig. 7 shows the OWFs power production during the simulation.

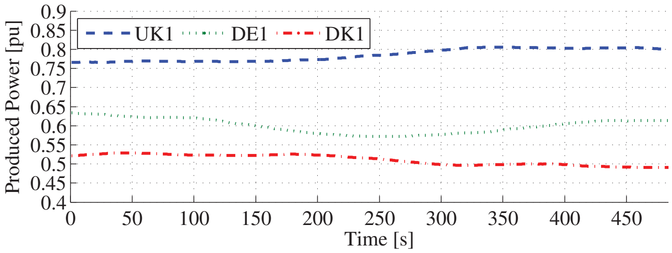


Fig. 7: Wind farms power production during the simulation.

Four different events are simulated to test the CARLAs ability to handle different system states. Table II describes the events, which deliberately occur at least two times to demonstrate the learning improvements made by the CARLAs. During the first event, $0 \leq t < 50$, it is assumed that no communication is performed, representing the worse case scenario for the DVC strategy.

TABLE II: Description of the CARLA states.

Sim. Time	System State (Event)
$0 \leq t < 50$	i: The OWFs production is unknown (no communication).
$50 \leq t < 100$	ii: The CARLA is minimizing the transmission losses.
$100 \leq t < 150$	iii: The UK requests 1 pu of power.
$150 \leq t < 200$	Same as ii.
$200 \leq t < 250$	Same as iii.
$250 \leq t < 300$	Same as ii.
$300 \leq t < 350$	iv: AC fault at the German onshore station.
$350 \leq t < 400$	Same as ii.
$400 \leq t < 450$	Same as iv.
$450 \leq t < 500$	Same as ii.

The simulation results are separated in two parts: first, the results of the dynamic simulation are given[2] and, later, the results of the CARLA optimization are discussed.

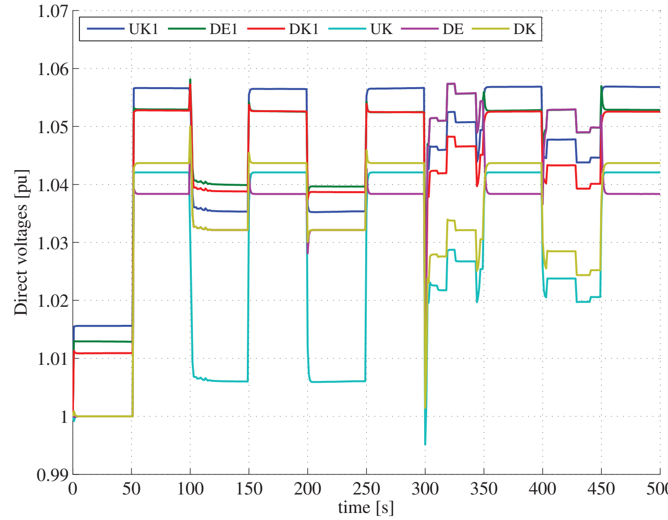
B. Simulation Results

The numeric simulation results are shown in Fig. 8, which displays the direct voltages at all the network nodes, the power transmitted to the onshore nodes and the transmission system losses.

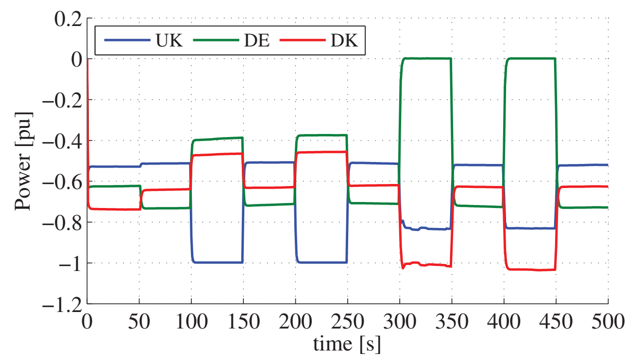
The DVC strategy is able to control the power flow in the MTdc network when the actual power production of the offshore wind farm is known. If communication is absent or fails, the method detects it and it operates the MTdc network with a flat profile strategy, i.e. the direct voltages at the onshore VSC terminals are set to 1 pu (this initial system state can be seen during the first 50 s of the simulation).

The optimization starts to operate at $t = 50$ s (system state ii) and the direct voltages at the onshore VSC terminals are raised so that the MTdc network losses are optimized, as shown in Fig. 8 (c). As a result, Germany receives more power than the other nodes. At $t = 100$ s, a new dispatch is made (system state iii) so that the UK node successfully receives 1 pu of power from the MTdc network. The second time this system state occurs, at $t = 200$ s, the CARLAs takes advantage of their previously knowledge and immediately apply optimized voltage values.

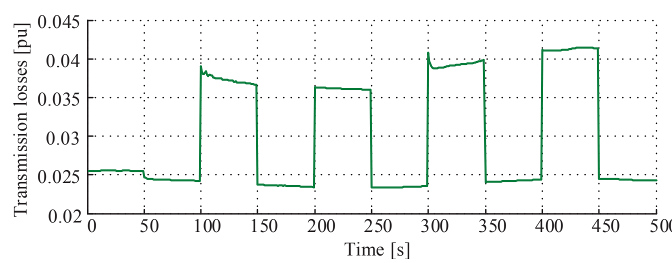
[2]The experiments were carried out on a 2.3 GHz Intel Core i7 MacBook.



(a) Direct voltages at the VSC-HVdc stations.



(b) Active power at the VSC-HVdc stations.



(c) Transmission losses in the MTdc network.

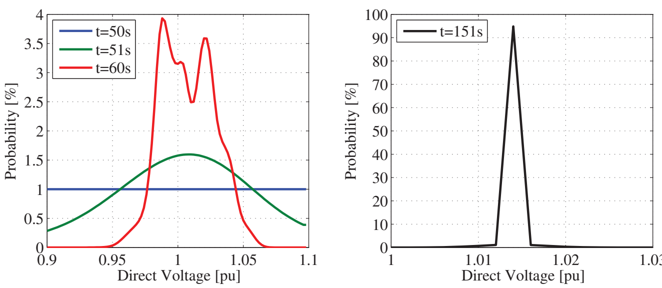
Fig. 8: Results from the numeric simulation.

When the German onshore node suffers from an ac fault (system state iv), at $t = 300$ s, the power flow in the MTdc network stays controlled. Throughout the numeric simulation, the DVC strategy minimizes the transmission losses while guaranteing that the power flows are feasible and that the rated powers of the VSC stations are respected.

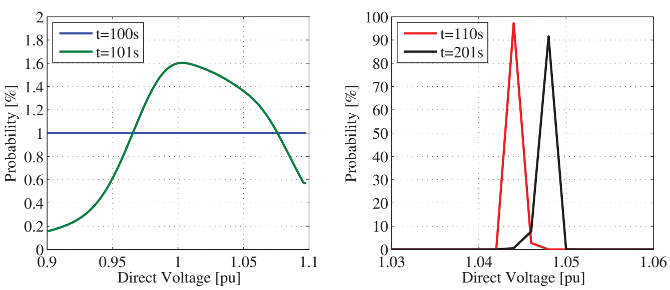
C. Reinforcement Learning

During the numeric simulation, the CARLAs satisfied all constraints whilst minimizing the MTdc transmission losses. On average, for each one second interval of the numeric simulation, the CARLAs evaluated the transmission losses and constraints circa 62 times. In this way, the CARLAs improved their CDFs every second before sending the direct voltage reference values to the onshore nodes according to the DVC strategy. The CARLA rapidly converges to a specific set of direct voltages, even though a decay function, displayed in (5), was applied to their CDFs.

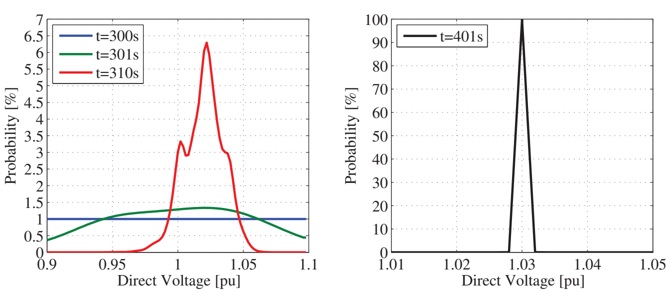
Fig. 9 shows the direct voltage distribution of a specific VSC CARLA for different time samples. To better demonstrate the learning process, the time samples were chosen as follows: seconds one, two and ten of the first time the system state occurred; and the first second when that system state reoccurred. Starting from a uniform distribution, the CARLAs start to converge over time to a specific set of direct voltages. Moreover, the distributions can adapt to wind changes, as shown in Fig. 9 (b), where the distribution of the German onshore node (DE) is shifted towards higher voltage values. The graphs are shown with different Y-axis scales in order to facilitate the visualization of the different distribution shapes. In late learning stages the distributions are concentrated over a narrow range of direct voltages.



(a) UK VSC normal operation CDF (state ii: $t \in \{50, 51, 60, 151\}$)



(b) DE VSC constrained operation CDF (state iii: $t \in \{100, 101, 110, 201\}$)



(c) DK VSC fault operation CDF (state iv: at $t \in \{300, 301, 310, 401\}$)

Fig. 9: Evolution of the CARLAs CDFs for distinct system states.

VI. Conclusions

This work has presented an application of RL techniques to a real-world application: the online control of MTdc networks for the integration of offshore wind energy generation. The DVC strategy while making use of RL techniques has superior capabilities: online controllability, optimization of a desired goal and constraints handling. Moreover the strategy is fast and able to perform online operation with an offshore power production sampling rate of, at least, 1 Hz. Different control policies were incorporated in the proposed control strategy. In this way, optimized power flows were achieved with lower computational power, when compared to control methods that make use of offline optimizers. Although, for improved performance, the DVC strategy requires the power production at the offshore wind farms to be communicated to the onshore stations, the strategy is capable of detecting communication failures and reacting appropriately by applying a flat profile to the MTdc network. The CARLAs algorithm demonstrated to be well-suited to adapt the direct voltage references of the onshore stations according to the OWFs power production and hence, to solve this stochastic problem. In conclusion, online control capabilities, power flow control and network security, among other features, make the proposed direct voltage control method well suitable to be applied in future MTdc networks.

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Appendix

```
procedure OPTIMIZE
    for each possible state s do
        // default to flat voltage profile
        archive_s ← ones(n)
        for each VSC station i do
            initialize CARLA_{s,i}
        end for
    end for
    while true do
        receive produced wind powers, identify state s
        if s ≠ previous s → decay CARLAs
        repeat
            for each VSC station i do
                trial_i ← sample CARLA_{s,i}
            end for
            // c(voltages) returns the constraint violations
            // p(voltages) returns the power losses
            if c(trial) < c(archive_s) or
               (c(trial) = c(archive_s) and
               p(trial) < p(archive_s)) then
                archive_s ← trial
            end if
            for each VSC station i do
                update CARLA_{s,i}, see equation (2)
            end for
        until new measurements are obtained
        send archive_s to onshore stations
    end while
end procedure
```

Fig. 10: Voltage profile optimization.

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