A general form of smart contract for decentralised energy systems management

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Abstract

Smart contract platforms have the potential to allow shared automatic control of energy transfer within networks in a replicable, secure, verifiable and trustworthy way. Here we present a general form of smart contract which captures the elements needed for shared control that will help formalise decentralisation. Two mechanisms were defined for agreement of control instructions for a Medium Voltage Direct Current (MVDC) link connecting two separately operated 33kV distribution networks. These were instantiated as smart contracts and were evaluated in terms of cost and the computational requirements for their execution. Real network and converter data from the ANGLE-DC demonstration project were used to model the MVDC link. We demonstrate that using smart contracts to agree control instructions between different parties is feasible. The potential for shared control using smart contracts gives operators and regulators a way of defining and decentralising operating responsibilities within energy systems.

Main

An energy system can be described as a collection of distinct networks, sources, sinks, their corresponding responsible parties, and the associated physical and information flows[1,2]. The information flows come from monitoring physical processes (e.g. voltage and current at a transformer) and decisions made by individual actors[3]. Information exchange interfaces are the mechanism by which information is passed between different responsible parties[4].

The complexity of energy networks is forecast to increase with higher volumes of information and numbers of controllable components[5]. When accompanied by decentralisation of responsibilities, this will lead to the creation of more information interfaces, or mean that more information must be processed at existing interfaces. An example of this, in electricity networks, is the possible transformation of Distribution Network Operators (DNOs) to Distribution System Operators (DSOs) in Great Britain (GB)[6,7]. As part of the transition, more localised balancing responsibility would be given to DNOs[8,9]. This would lead to a requirement for more complex agreements at interfaces (e.g. between two distribution networks or between a distribution network and a transmission network) as neighbouring parties will rely more on the predictable behaviour of adjacent networks[10]. This leads us to ask what standardised rulesets at the interfaces between responsible parties, if any, would make the operation and planning of energy systems more secure and lower cost.

The emergence of smart contract platforms (often under the rubric of Distributed Ledger Technology[11] or Blockchain Technology[12]), brings the opportunity to securely automate many of the procedures that take place at interfaces and potentially to lower the whole system cost[11]. The concept of smart contracts, self-enforcing agreements in the form of executable programs[13], originating with Szabo in 1994[14], provides a means of setting out negotiation and self-enforcing settlement rules that operate with a high degree of trust. They are replicable, secure and verifiable[15–18]. A simple smart contract rule might be "if X happens, pay Y to account Z." A crucial innovation is the self-enforcing nature of the "pay" statement. In the example, "X" is a digitally encoded event derived from a sensor reading. Therefore the trustworthiness of any smart contract scheme is ultimately dependent on the trustworthiness of sensors, and the encoding and transmission of information. Furthermore, the position of smart contracts within existing legal systems is the subject of active research and consideration[19–21]. Smart contracts are well suited to enact agreements for shared control of energy transfer processes, where the decision makers are located within different organisations (or sub-divisions of the same organisation).

Examples of shared energy transfer processes in electricity networks include control of elements such as; switches, transformer tap changers, or power electronic converters forming a DC-link. DC-links allow the precise control of energy flows between electricity circuits and, combined with smart contracts, offer the potential to clearly delineate responsibility for the operation and control of distinct segments of electricity networks. The potential for DC-links to reduce network costs, through control of active and reactive power set-points is well documented[25–31]. DC-links also have the potential to decouple networks, and therefore clearly define responsibility for system frequency and, by extension, system stability[26,32,33]. In a GB context, this would allow the DNO to DSO transition to occur at increased granularity, separated by voltage level and DC links. The use of smart contracts, to share control of DC-links or similar elements, therefore has the potential to limit unforeseen complex control interactions between energy systems. Furthermore, due to the self-enforcing nature of smart contracts, agreed rules for shared control can be instantiated in a way that is less susceptible to tampering and less reliant on traditional methods for pursuit of transgressions. Alternatives such as control solely using sensor measurements[22,23], or single-party control using a Distribution Management System (DMS)[23,24], are prone to manipulation by one or more participants.

The motivation behind this work is to establish how system operators, and other participants, should conceptualise the application of smart contracts within energy systems. In doing this, consideration must to given to the common characteristics such smart contracts have as well as how participants interact with them. In general, when two or more energy systems, with different responsible parties, are connected by the same controllable process, the question of what control set-point should be selected in any situation is raised. Therefore, the particular research questions we address are, what general form could smart contract based shared control agreements take, and can example smart contract rules for shared control of an energy transfer process, a DC-link, be defined and demonstrated.

Here we set out a general form of smart contract for shared control of energy transfer processes, applicable at any scale of energy system with digital monitoring and control. The general form consists of 6 stages; deposit, setting of preferences, negotiation, instruction of process, settlement, and withdrawal. We instantiate the general form contract using two defined rulesets for the shared control of a modelled MVDC link and, through demonstration using an emulated smart contract platform, we show that that using smart contracts to agree control instructions between different parties is feasible.

A general form of smart contract for shared control

The proposed general form of smart contract for negotiation and settlement of controllable processes between two or more responsible parties is shown in Figure 1. We categorise information flows within the responsible parties in 3 layers; data processing, decision support, and decision making. The data processing layer is the interface with physical equipment (e.g. metering) and procedures (e.g. maintenance schedules). It includes collection, compression and storage of data. The decision support layer includes the presentation of information to decision makers after analysis of available data. An example is cost minimising optimisation. The decision making layer is where the decisions in relation to a controllable process are made. We define agreement interfaces as the locations where a decision maker in one responsible party must come to an agreement with a decision maker in another responsible party.

The presented conceptual framework builds on the Smart Grid Architecture Model's (SGAM) definition of interoperability[34]. In the SGAM, interoperability is defined as the exchange of information between two or more systems to cooperatively perform a specific function. In our framework, the information exchange and the control function are integrated by a smart contract that instructs a physical process. The proposed framework defines a general form smart contract to perform the shared control function. It also categorises the information collection and analysis that leads to the presentation of information to the shared control smart contract.

Model, negotiation rules and scenarios

Here we instantiate the general form smart contract using the example of an MVDC link connecting neighbouring electricity networks with different responsible parties. Shared control of the active power setting is achieved using smart contract based negotiation. We use real network and converter data, and deploy a smart contract running on an Ethereum[35,36] Virtual Machine (EVM), to form an overall model (Fig. 2).

MVDC links are only beginning to be used[37,38], so our data was sourced from a demonstration project, the ANGLE-DC project, where an MVDC link will connect the Isle of Anglesey to mainland North Wales[39–41]. The proposed link will operate at ±27kV DC and connect two 33kV AC networks, with converter ratings of 30MVA. Presently, the island network has a large amount of embedded generation; three wind farms with a total capacity of 34.7MW, and two solar farms with a total capacity of 28.5MW. Both of the 33kV AC networks are under the jurisdiction of a single responsible party, but we model two separate responsible parties, designated Network 1 and Network 2.

To demonstrate how separate parties can achieve shared control of the MVDC link, both of the electricity networks were first modelled using a Newton Raphson based load flow method for three scenarios; normal (N), high demand (D), and high generation (G), see Figure 2. A simplified operational cost model, based on resistive losses, line utilisation and extent of deviation from nominal voltage, was used to model the costs incurred by each network operator across a range of possible MVDC-link active power set-points. These modelled costs were used as the basis for choosing the input preferences to a smart contract.

The problem, of defining the negotiation rules for the MVDC link's active power set-point, is formulated as two questions; what rules should be used to select one of a range of set-points and how the network operators should express their preferences for each of the possible set-points. To do this, the MVDC-link's active power operating range is divided into 13 options, formed by twelve 5MW wide bins and a 0MW option. Two methods for expression of the set-point preferences are used. The first has the network operator submit offers (bids) for each of the options. The second requires the network operators to rank the options in order from most favourable, to least. As a result, two rulesets are created for negotiation of the MVDC link's active power set-point; "Highest Combined Offer" (HCO) and "Ranked Preference Selection" (RPS). The intention behind HCO was to approximate the optimal set point for the ensemble of the two networks (assuming both networks have complete cost information for each prospective set-point and bid rationally). In contrast the intention behind RPS was to find a trade-off set point where the two networks have equal negotiation weight.

The HCO smart contract accepts offers (bids) for each option, sums the offers from both networks for each option, and selects the option with the highest combined offer. The highest bidder for the selected option pays the lowest bidder the difference between the bids for the selected option. The highest bidder then chooses the final operating point within the selected bin (submitted prior to negotiation). In the case that two bins receive the same highest combined offer, one of the networks is given authority to select the operating point. This selection authority alternates between the networks every time it is used.

The RPS smart contract accepts a ranked preference list from 1 to 13 (1 is most favourable, 13 least) from both parties, pairs the preferences, and selects the pairs such that there are no other pairs in which both parties have more favourable options. Where this results in more than one pair, one of the networks is given authority to select the operating point. This selection authority alternates between the networks every time it is used. The two algorithms are compared in Figure 3 and they are formally specified in the Methods section.

The inputs to the contracts, shown in Figures 4 and 5, are calculated based on a comparison of the operating costs at each DC-link power set point for 48 half hour periods for the three scenarios (N, D and G). The modelled network operation costs are translated into offers (in the case of HCO) or preference rankings (in the case of RPS). These are shown as heat maps in Figures 4 and 5, with each network's preferred operating point represented by the red lines. Using these data, the smart contracts were tested with the nine combinations of network loadings (N-N, N-D, N-G, D-N, D-D, D-G, G-N, G-D and G-G).

Smart contract execution

The HCO and RPS smart contracts were written in the Solidity smart contract language, for execution on an Ethereum Virtual Machine (EVM). A deposit function was included and two deposit accounts were maintained. In the case of the HCO contract, the deposit amounts were adjusted based on the payment requirements (the difference between the offers at the selected operating point). The testing environment utilised is shown in Figure 6. It includes an emulated Ethereum blockchain created with TestRPC. This was interfaced using Python[42,43] with Numerical Python[44], Pandas[45], Matplotlib[46] and Web3.py.

The computational cost of running the contract on the public Ethereum smart contract platform was calculated as a proportion of the present limit[47]. The HCO contract would use 0.15% of the total half hourly capacity and the RPS ruleset would use 0.09%. There is scope for optimisation of our smart contract code, and the pre-input data submission formats. Therefore, in practice, a lower cost of computation could be expected. It is well known, however, that blockchain implementations sometimes have relatively high transaction costs. The example was of steady state control of a discrete element within a power system. It is therefore possible to create multiple instances (e.g. for different DC-links) across different platforms, allowing the parties to select the smart contract platform based on transaction, running, or implementation costs. Furthermore, a default operating point selection could be added to the smart contract negotiation rules, for the case where transaction costs exceed an agreed threshold.

A sensitivity analysis was conducted to assess how varying the number of possible set-point options affects the computational cost, see Figure 7. It was found that the computational cost of the HCO algorithm scales linearly with the number of bins. In contrast, the RPS contract's computational cost scales exponentially with the number of bins. This is likely to be due to the nested for loops within the RPS implementation. When the number of bins is lower than or equal to 43, the computational cost of the HCO contract is higher than the RPS contract.

The scaling of computational cost with negotiation frequency is more straightforward. Each negotiation and settlement period requires two transactions (instructions to run the smart contract code, paid for by the originator), one from each network operator. Increasing the rate of set-point negotiations therefore requires a further two transactions for each additional negotiation period. It might be expected that decreasing the bin width and the negotiation period would result in lower network costs due to increased precision in mapping of costs to prospective operating points. In practical application, a cost-benefit analysis should be undertaken to estimate the optimum bin-width and negotiation frequency.

Performance of the smart contract negotiation algorithms

Figure 8 shows the active power set-points selected by the HCO and RPS contracts for each of the network loading scenarios (N, D, G). Figure 9 shows the total modelled cost saving across both networks with the smart contract algorithms, relative to the situation with no DC-link installed. Note that this does not include the computation cost of running the smart contract and the operational cost model does not reflect the true whole system cost. To achieve a whole system cost evaluation, an exogenous model evaluation and validation would need to be conducted that establishes the validity of the whole system model and its cost data. However, our simplified model is suffice to establish the principle of shared control through smart contracts and to compare the performance of the two presented algorithms.

In comparing the HCO and RPS rulesets, we observe that the HCO contract always selects the active power settings with the lowest total modelled operational costs for the networks. In contrast, the RPS contract often deviates from the lowest total modelled cost, especially where the preferences are different, such as the case when Network 1 has high loading. This is reflected in the disagreement in selected operating points in Figure 8 and is particularly noticeable when Network 1 experiences high loading (central column in Figure 8).

The benefit from reducing the total modelled costs of the two networks was not evenly shared. With the HCO contract, Network 1 would incur a relatively large cost for a non-preferred operating point, therefore it puts in relatively high bids to avoid the possible selection of the non-preferred option. This means that it always pays the less sensitive network (Network 2). Consequently, in the test scenarios, Network 1 often has higher modelled costs than if no DC-link were installed (with its counterpart, Network 2, being the beneficiary of the reduction in the total modelled operational costs). We suggest that, in practice, Network 1 would assess that the risk, of its neighbour making a competitive offer for its preferred operating point, is low, and that it could therefore reduce its offers significantly. In contrast to the HCO ruleset, the RPS ruleset gives equal weighting to the preferences of both network operators. No payment is made between the parties. Therefore, whilst both networks have lower modelled costs than in the case with no DC link, Network 2 can inflict costs on Network 1 with little risk when the RPS contract is used.

Discussion

We foresee a growing research field around the concept of shared control through smart contracts. Areas for further development include smart contract algorithm design and implementation as well as methods and techniques for integration with control and metering hardware. Here, shared control of a power electronic based DC-link was chosen as the control element, but the presented algorithms could also be applied to AC control elements with direct control over the active power settings. Furthermore, the general approach could be used to share control of any element that has influence over two or more networks with different responsible parties; transformer tap changers, for example. The approach could also be applied where there are more than two parties (n>2). A realistic case would be multi-terminal DC-links located at the intersection of three or more distinct networks.

Further analysis, including with the network operators adopting co-operative, adversarial and indifferent strategies (for the input of preferences to the shared control smart contract) should be undertaken. This analysis must also account for the operation of the physical networks. For instance, if one network operator does not like the selected MVDC link operating point, what stops it from isolating the busbar and making power transfer impossible? This could be solved through inclusion of a meter-linked penalty function in the smart contract. For example, if one network does not allow power transfer this would be detected at the DC link and a pre-agreed penalty fee automatically transferred.

The two presented smart contract algorithms have been shown to function. In the presented arrangement, each network operator has incentive to ensure that their preferences reflect the constraints of their network. With the HCO algorithm for example, this would result in relatively high bids for set-points that do not cause constraints to be exceeded. If an undesirable set-point (e.g. one that would, without intervention, result in a costly voltage excursion) did get selected (through the other operator bidding highly for it), then it would be the duty of the first network operator to accommodate the selected setting. In our example, the cost of this is simulated using a simplified electricity network operation cost model. A potentially beneficial effect of the arrangement is to increase the incentive for the network operators to accurately predict their prospective costs and to map them to the prospective shared control set-points. This should result in responsible parties seeking things that improve the predictability of their network (e.g. active network management, advanced prediction software, energy storage, co-operative relationships with neighbours) and, ultimately, lead to a more resilient system.

Regulatory or system governance intervention will likely be required to make use of smart contracts for shared control of interconnecting processes, such as the DC-link example presented here. In our example, Network 1 sometimes had higher costs than it would have had with no DC-link (with Network 2 being the beneficiary). Whilst, in practice, this may result in one network reducing its offers over time, it may also dissuade network operators from creating such links (despite the potential for overall operational cost reduction) in the first place. Therefore, given energy networks are natural monopolies, regulatory intervention may be required to stimulate the interconnection of networks in the way set out here.

We conclude that smart contract based shared control of energy infrastructure is feasible. The general conceptual framework that was presented captures the elements needed in smart contracts for shared control. The work demonstrates two algorithms for smart contract based shared control of DC-link active power between two electricity networks. The conceptual framework, and the demonstrated operation with a DC-link example, show a way to share control of energy network assets and establish a means for system operators, and other participants, to conceptualise the application of smart contracts within energy systems. The use of smart contracts for shared control gives participants and regulators a tool for the delineation of responsibilities in energy systems.

Methods

Selection based on the highest combined offer

In this ruleset, both the network operators are required to submit offers for each active power set-point bin for a given time window. The offers are in monetary units, denoted as

$$\boldsymbol{O}^{i,t} = \{O_b^{i,t} \mid b = 1, 2, ..., |\boldsymbol{B}|\} \quad \forall i \in \boldsymbol{I}, t \in \boldsymbol{T} \text{ ,} \tag{1}$$

where O represents an offer and $\boldsymbol{O}$ is the set of offers; i is the index of a network operator, and $\boldsymbol{I}$ is the set of all the participating network operators (in this paper $|\boldsymbol{I}| = 2$); t is the index of a time window, and $\boldsymbol{T}$ is the set of all the time windows considered; b is the index of the active power set-point bin, and $\boldsymbol{B}$ is the set of all the bins. The network operators are free to make any offer for any bin, provided that adequate deposit has been made.

Once the offers have been received, the bin with the highest summed offer is selected, i.e.

$$b^* = \arg\max_{b \in \boldsymbol{B}} \sum_{i \in \boldsymbol{I}} O_b^{i,t} \tag{2}$$

where b^* represents the set-point bin finally selected. The consideration behind this design is to maximize the overall benefits of interconnected networks. b^* is found using the following algorithm:

Algorithm 1: Selection based on the highest combined offer (HCO)

INPUT: $\boldsymbol{O}^{i,t}, \boldsymbol{B}$

OUTPUT: b^*

START

$c^{\max} = 0$ // $c^{\max}$ stores the maximum value of the summed offers

for $b = 1$ *to* $|\boldsymbol{B}|$ **do**

  $c = O_b^{1,t} + O_b^{2,t}$ // c is a temporary variable to store the summed offers at a setpoint bin

  if $c > c^{\max}$ **do**

    $c^{\max} = c$

    $b^* = b$

  end if

end for

return b^*

END

After b^* is selected, the network operator with the higher offer at b^* is required to pay the other network operator the difference of the offers at b^*, and gets the right to decide the exact operating point within the bin, i.e. to instruct the DC link controller during operation. Finally, note that the network operators are free to pick the reactive power operating points, as long as they are within converter constraints.

Ranked Preference Selection

In this ruleset, each network operator is required to submit a preference list for active power set-point bins for a given time window. The list consists of ordered preferences, denoted as

$$\boldsymbol{P}^{i,t} = \{P_b^{i,t} \mid b = 1, 2, ..., |\boldsymbol{B}|\} \quad \forall i \in \boldsymbol{I}, t \in \boldsymbol{T} , \tag{3}$$

where $P_b^{i,t}$ represents the preference of the network operator i for the set-point bin b for the time window t. Note that $P_b^{i,t}$ is an ordinal number, for which the lower value represents higher preference.

Once the preference lists have been received, the preferences for each bin are paired (e.g. $P_b^{1,t}$ and $P_b^{2,t}$ are paired as < $P_b^{1,t}$, $P_b^{2,t}$ >). Then the Pareto subset of all the pairs, consisting of all the non-dominated pairs, is identified, and the bins corresponding to the elements of the Pareto set are taken as the candidates for the final set-point bin. The consideration behind this design is that the preferences of both the network operators are equally important, so only the undesirable bins, where there exists a possible set-point that is preferable (more highly ranked in their preference list) to *both* network operators, are ruled out. Formally, the candidate bins, denoted as $\boldsymbol{b}^*$, are the solutions (i.e. Pareto optima) of a two-objective optimization problem:

$$\begin{aligned} &\boldsymbol{b}^* = \arg\min_{b \in \boldsymbol{B}} \left(f_1(b), f_2(b) \right) \\ &f_1(b) = P_b^{1,t} \qquad , \\ &f_2(b) = P_b^{2,t} \end{aligned} \tag{4}$$

where $f_1(b)$ and $f_2(b)$ are the two objectives, i.e. the mapping between the set-point bins and preferences.

$\boldsymbol{b}^*$ is determined by comparing each pair of preferences, < $P_b^{1,t}$, $P_b^{2,t}$ >, with all the others; if the pair is lower ranked than some other pair for both the operators, it is dominated and should be ruled out. In contrast, if the pair is not lower ranked than any other pair for both the operators, it is a non-dominated pair and should be added as an element of $\boldsymbol{b}^*$. The following algorithm is used to find $\boldsymbol{b}^*$:

Algorithm 2: Ranked Preference Selection

INPUT: $\boldsymbol{P}^{i,t}$, $\boldsymbol{B}$

OUTPUT: $\boldsymbol{b}^*$

START

for $b = 1\ to\ |\boldsymbol{B}|$ **do**

  $s = 0$ // s is a flag indicating whether the bin b is dominated: "1" for dominated; "0" for non-dominated

  for $b' = 1\ to\ |\boldsymbol{B} \setminus \{b\}|$ **do**

    if $P_{b'}^{1,t} < P_{b}^{1,t}\ \&\ P_{b'}^{2,t} < P_{b}^{2,t}$ **do** // $\&$ represents the logical operator "and"

      $s = 1$

      break // Exit the current "for" loop

    end if

  end for

  if $s = 0$ **do**

    $\boldsymbol{b}^{*} \leftarrow b$ // $\leftarrow$ is the operator that puts the right-side element into the left-side array

  end if

end for

return $\boldsymbol{b}^{*}$

END

If the candidate setpoint bin, $\boldsymbol{b}^{*}$, includes only one element, then the sole element is naturally the final set-point bin; but if $\boldsymbol{b}^{*}$ includes multiple elements, the final set-point bin is selected by one of the networks. The authority to make this final selection alternates between the networks every time it is used. It may be preferable to select the final set point through random selection from the Pareto optimal set, as opposed to alternating selection authority. However, due to the relative expense of random number generation using smart contracts, this was not used. Finally, both the operators are free to pick the reactive power operating points, within converter constraints.

Simplified model of Network Operator costs

The MVDC link was modelled using a steady state approach. The two networks were modelled using a fast-decoupled Newton Raphson based load flow method (IPSA software was used), the network models have been described in prior work[37]. This was then used to calculate cost of operation for each of the networks at each active power set-point. These costs were then converted into offers, or ordered preferences, for use as inputs for the smart contracts.

MVDC link model

Voltage control mode was selected for the MVDC link. This allows the active power of the MVDC link to be determined by instruction from the smart contract and for the reactive power at both terminals to be automatically adjusted (e.g. at the tertiary control level) to maintain the voltage at a specified value, 1 p.u. A mathematical model of the MVDC link was developed by considering the constraints of the VSCs:

Active power constraints:

$$P_{VSC1} + P_{VSC2} + P_{DC-loss} = 0 \qquad (5)$$

where P_{VSC1} and P_{VSC2} are the active power flow through each VSC. $P_{DC-loss}$ is the loss within the DC link, which is relatively low (approximately 1 ~ 2% of the active power flowing through the DC link) compared to the total losses within the network. Therefore, $P_{DC-loss}$ is neglected, and Equation (5) is simplified as:

$$P_{VSC1} = -P_{VSC2} \qquad (6)$$

Reactive power constraints:

The reactive power is considered as it influences the modelled operational cost of the networks. After the active power set-point has been selected by the smart contract, each network operator is able to select the reactive power, within the capacity constraints of its connected converter. The reactive power constraints are defined by:

$$Q_{VSC,n}^{min} \leq Q_{VSC,n} \leq Q_{VSC,n}^{max} \quad (n = 1,2) \tag{7}$$

where $Q_{VSC,n}$ is the reactive power at n^{th} terminal of the DC link. $Q_{VSC,n}^{min}$ and $Q_{VSC,n}^{max}$ are the lower and upper limits of reactive power provided by the VSC at terminal n, the modelled MVDC link is two terminal so n is no greater than 2. $Q_{VSC,n}^{max}$ is positive, indicating that reactive power is injected to the network, and $Q_{VSC,n}^{min}$ is negative, indicating that reactive power is absorbed from the network.

Capacity constraints:

The converter capacity constraints are defined by:

$$\sqrt{P_{VSC,n}^2 + Q_{VSC,n}^2} \leq S_{VSC,n} \; (n = 1,2) \tag{8}$$

where $S_{VSC,n}$ is the rated capacity of the VSC at n^{th} terminal of the DC link, the modelled MVDC link is two terminal so n is no greater than 2.

Network operation cost function

The operational costs of the network at each end of the MVDC link include the energy losses, as well as the equivalent cost from overloading and voltage violations. Here, a cost to maintain a relatively balanced loading between branches is assigned to the line utilization index, and a cost to maintain a relatively consistent voltage profile (voltages close to the nominal values) is assigned to the voltage profile index. A weighting factor is used for each of the three elements in order to calculate the total cost for operating the network. As the MVDC-link active power set-points vary, the line currents and node voltages are affected. The voltages and currents are used within the power loss, line utilisation and voltage profile index calculations.

$$f = f_{1,\mathrm{t}} \times Pr1 \times w1 + f_{2,\mathrm{t}} \times Pr2 \times w2 + f_{3,\mathrm{t}} \times Pr3 \times w3 \tag{9}$$

where $f_{1,\mathrm{t}}$ is the power losses at time t, $f_{2,\mathrm{t}}$ is the line utilization index, and $f_{3,\mathrm{t}}$ is the voltage profile index. $Pr1$, $Pr2$ and $Pr3$ are the prices for power losses, loading and voltage profiles respectively and $w1$, $w2$, and $w3$ are the weighting factors of the three elements considered. The detailed expression of f_1, f_2 and f_3 are:

$$f_{1,t} = \sum_{k=1}^{N_{branch}} I_{k,t}^2 \times r_{k,t} \tag{10}$$

where the active power losses in feeder lines and transformers of a network were considered. $I_{k,t}$ is the current flowing through branch k. $r_{k,t}$ is the resistance of that branch, and N_{branch} is the total number of branches including lines and transformers.

$$f_{2,t} = \sqrt{\frac{\sum_{k=1}^{N_{branch}}\left(\frac{I_{k,t}}{I_{k,rated}}\right)^2}{N_{branch}}} \tag{11}$$

where $I_{k,t}$ is the apparent power flow in branch k at time t, and $I_{k,rated}$ is the rated current of the branch. N_{branch} is the total number of branches. The line utilization index reflects the average degree of utilization of all feeder lines in a network, it reflects the costs associated with a network with limited available capacity. These costs arise from the requirement to perform costly actions (e.g. curtailment of generation or load) where line utilisation is high.

$$f_{3,t} = \sqrt{\frac{\sum_{i=1}^{N_{bus}}(V_{i,t}-V_{i,rated})^2}{N_{bus}}} \tag{12}$$

where the improvement of voltage profiles can be achieved by minimizing the voltage profile index. $V_{i,t}$ and $V_{i,rated}$ are the real and nominal voltages at bus i. N_{bus} is the total number of buses. The voltage profile index reflects the mean deviation of all bus voltages from the nominal value (1 p.u.).

Translation of modelled costs into smart contract inputs

The modelled costs were translated into inputs for the HCO and RPS smart contracts. For the HCO smart contract, the offer made by a network operator for any given operating point range (bin), is the difference between its modelled cost for that bin and its highest modelled cost found in the entire range of prospective operating points. The bin with the highest modelled costs therefore has an offer of zero. For the RPS smart contract, the costs for operation in each bin were ranked from least costly to most costly.

Smart contract EVM computation cost

The accumulated GAS (the unit for computational work on the EVM) was recorded for each of the transactions (sending the offers to the contract and instructing it to calculate the active power set point) and used as the measure of proportional computing cost, relative to the block GAS limit (presently[47] 8,000,000) of the public Ethereum platform. The mean computational cost for a transaction used with the HCO ruleset (selecting from 13 active power bins) was 19.6% of an individual block limit. The mean computational cost for a transaction used with the RPS ruleset was 11.7% of the individual block limit. The contracts used 2 transactions per half hourly period, and, assuming a 14 second period between blocks, the HCO ruleset would use 0.15% of the total public Ethereum platform's present EVM computation capacity over each half hour; the RPS ruleset would use 0.09%.

Sensitivity Analysis

To assess the scaling complexity of the HCO and RPS algorithms, the test procedure was repeated with increasing numbers of bins (set-point options). The total computational cost of all of the transactions was assessed against the number of bins. The results are shown in Figure 7.

Code Availability

Information about the code used in this research, including how to access it, can be found in the Cardiff University data catalogue at http://doi.org/10.17035/d.2018.0064088749.

Data Availability

The data that support the plots within this paper and other findings of this study are available from the corresponding author upon reasonable request. Provision of the underlying electricity network data is subject to the permission of Scottish Power Energy Networks. However, the modelled power network cost data are provided as supplementary data, allowing the results to be recreated.

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Individual contributions

L.T. Conceived the paper, wrote the code and drafted the manuscript.

Y.Z. Conceived the Ranked Preference Selection rules, formally defined the negotiation rules in the methods section, and made improvements to the manuscript.

C.L. Performed the cost analysis of the electricity networks, wrote up the relevant part of the methods section, and made improvements to the manuscript.

J.W. Made improvements to the manuscript.

N.J. Made improvements to the manuscript.

Competing interests

Lee Thomas has a small number of Ether, the token used by the Ethereum platform. The remaining authors have no competing interests.

Figure legends

Fig. 1 | General form of smart contract for shared control of an energy transfer process. The deposit stage requires both parties to prove that they have adequate currency to cover the negotiation outcome. If one party does not, then control of the shared process reverts to the other party. The setting of preferences includes the communication of how much each operating point is desired. Following this, in the negotiation stage, the contract runs a pre-agreed set of rules on the preferences and delivers a selected operating point. This is used to instruct the physical hardware in the instruction of process stage. In the settlement stage, the contract runs a set of rules to calculate any peer to peer payments, based on the negotiation and actual operation. Finally, the smart contract includes a means of withdrawing the deposit and, if included in the rules, any peer to peer payments

Fig. 2 | Model architecture for the simulated smart contracts. The normal scenario combines the source demand data (red dash-dot) and generation data (green dash). The high demand scenario was created by multiplying the demand in the normal scenario by three. The high generation scenario was created by multiplying the generation in the normal scenario by three.

Fig. 3 | A simplified example of the implemented rulesets for a given time window. The middle bin at 0MW is shown as 5MW wide for clarity. A "zero width" bin (a single 0MW option) was actually used, bringing the converter range to ±30MW. The HCO algorithm selects the bin with the highest combined bid from both network operators. The RPS algorithm first selects the bin with the lowest summed rank from the options where there are no other ranked set-point preference pairs in which both parties have more favourable options. If there is more than one option in this "pre-selection" set, the final selection is made by the network operator with selection authority (which alternates between the operators). Brackets indicate the ranking of each network's set point preferences in the RPS contract.

Fig. 4 |Offers (bids) sent to the HCO smart contract. The y-axes indicate the prospective operating point of the MVDC-link (divided into bins). The x-axes indicate the time of day (half hour number). The colour indicates the size of the bid for a particular operating point for a given half-hour period. The colours are normalised (made proportional to the maximum offer for the day). The red line is the lowest cost operation. N, D, and G refer to the normal, high demand, and high generation scenarios.

Fig. 5 | Ranked set-point preferences sent to the RPS smart contract. The y-axes indicate the prospective operating point of the MVDC-link (divided into bins). The x-axes indicate the time of day (half hour number). The colour indicates the preference order for each operating point for a given half-hour period. The colours are normalised (made proportional to the maximum offer for the day). The red line is the lowest cost operation. N, D, and G refer to the normal, high demand, and high generation scenarios.

Fig. 6 | Overview of smart contract development and testing tools. The modelled smart contracts were executed on the TestRPC based EVM. The smart contracts, written in the Solidity language, were compiled using the Remix development environment. Contract deployment, deposits, and the communication of network operator preferences were done with transactions prepared using the Web3.py client. Modelling of the electricity networks was done using IPSA.

Fig. 7 | Scaling of computational cost against number of bins for the HCO and RPS algorithms. The total computational cost of all transactions across all of the tested scenarios, half-hourly negotiation, with an increasing number of set-point options (number of bins).

Fig. 8 | The MVDC link operating points selected by the smart contracts. The y-axes are the selected active power setting of the DC-link (positive is from Network 1 to Network 2) and the x-axes are the time of day (half hour number). N, D, and G refer to the normal, high demand, and high generation scenarios. HCO and RPS indicate the output from the Highest Combined Offer and Ranked Preference Selection smart contract algorithms. “RPS pre-selection” indicates those active power set-points with the lowest summed rank where there are no other ranked set-point preference pairs in which both parties have more favourable options.

Fig. 9 | Modelled total network operation costs with shared control (relative to the case with no DC-Link). The y-axes are the modelled operational cost for the selected DC-link active power as a proportion of the modelled operation cost for the case with no DC-link. The x-axes are the time of day (half hour number). N, D, and G refer to the normal, high demand, and high generation scenarios.