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A plug and play artificial intelligent architecture for smart local energy systems integration

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Executive summary

For a smart local energy system (SLES) to be truly 'smart' it must be capable of managing complex interactions between data, users, and the physical devices which make up the network, while also meeting the key criteria of flexibility, scalability, and reusability. Artificial intelligence (AI) techniques can be utilised to achieve this, and thus make SLES both more effective and more efficient.

While technological limitations are often cited as a barrier to SLES, there are existing, mature, technologies like multi-agent systems (MAS) which can allow for plug and play (PnP) capabilities to be added to existing systems.

To investigate this potential, an MAS approach was taken to facilitate the trading of energy between a range of simulated SLES units. This solution was successfully deployed on top of the existing control system for each of these units.

This application of existing AI techniques and designs to enhance an existing smart gird demonstrator allowed the demonstrator to better achieve the aims of an SLES specifically providing for flexibility, scalability, and reusability.

This investigation showed the following:

- The use of MAS to allow inter-unit energy trading brought down the costs of balancing the individual smart local energy systems by 10%-15%, while also increasing their income by between 15%-25%. This was done by reducing reliance on the wider grid.
- The MAS solution was demonstrated to build scalability in the intelligent power management system. Outcomes improved for each unit as more units took part in the inter-unit trading. It ranged from ~75% utility with 2 units to ~90% utility with 10 units.
- The MAS architecture design took a flexible PnP approach, which could accommodate new market participants joining while others left over time, and could accommodate a range of technology options.
- The MAS design provides for reusability, and could be deployed in a number of locations where SLES are interconnected.

Introduction

1.1 Aim

The aim of this work was to demonstrate the use of existing advanced AI techniques to expand the functionality of an existing smart grid platform through the development of a flexible and extendable architecture. This document sets out pertinent background information, the specification of the problem, a case-study on how this problem was solved, and the lessons learned from this solution.

The ADEPT (ADvanced multi-Energy management & optimisation time shifting PlaTform) demonstrator was used as a case study to prove that MAS can be used to build flexibility into intelligent power management systems. This demonstrator is an industrial microgrid, and includes a wind turbine, a PV system, and battery storage, that serves a mixture of industrial and residential loads.

1.2 Background

1.2.1 Multi-agent systems

MAS were selected for this project, as they provide opportunities for architectures that make use of decentralised processing and control, allowing for dynamic system integration such as that required by the ADEPT extension.

Intelligent agents, as used in MAS, have three significant characteristics that distinguish them from other agent-based systems (Wooldridge, 1999):

- **Reactivity** – the ability of agents to react to changes in environment quickly, by taking actions based on those changes and its desired function
- **Pro-activeness** – intelligent agents can dynamically change behaviour to achieve their goals
- **Social ability** – intelligent agents can communicate with other intelligent agents directly, collaborating and negotiating to achieve their own goals.

MAS are comprised of a collection of agents communicating and interacting in the same environment (Catterson et al, 2011). Each agent exists in the same environment, with its own goals and capabilities, but the system itself has no global goal. This means MAS must be designed so that agents' local goals are consistent with the overall intention of the system designer (McArthur et al, 2007). This autonomy allows for agents to co-operate and co-ordinate to achieve their individual goals. In addition, the independence of agents and their goals allows for MAS to be extendable and adaptable, as agents in the system can adapt to the removal or modification of existing agents, or addition of new agents (Catterson et al, 2011).

Applications of MAS have been demonstrated, with a number of functions pertinent to energy, and multi-energy systems. These include

- Brokerage of energy markets (Rodríguez González et al, 2019);
- Flexible dispatch of energy resources (Zeng et al, 2019);
- Facilitation of peer-to-peer energy trading (Satheesh Kumar and Nagarajan, 2019);
- Active network management, including for system restoration (Dong et al, 2018), voltage regulation (Davarzani et al, 2019), under-frequency load shedding (Santos et al, 2019) and condition monitoring (McArthur et al, 2019);
- Estimation of network parameters and constraints (Huang et al, 2019);
- Demand response management (Davarzani et al, 2019), control of hydro-electric resources(Satheesh Kumar and Nagarajan, 2019), electric vehicle grid integration (Lakshminarayanan et al, 2019), combined heat and power operation (Liu et al. 2018), and multiple energy carrier microgrids (Moghaddas-Tafreshi et al, 2019).

Of these applications, peer-to-peer energy trading and microgrid control are the most relevant to this project, although all have applications for SLES.

1.2.2 MAS for Smart Local Energy Systems

Three key requirements of SLES are particularly well met by the capabilities of MAS:

- **Flexibility** – SLES can expect throughout their lifecycles to be required to deal with expanding and changing use-cases, the connection of new devices and device types (and disconnection of old devices), and the inclusion of traditionally separate energy vectors into the functioning of the system.
- **Scalability**- SLES have to be capable of adapting to increases in both energy delivery devices, and in loads, including new types of both.
- **Reusability** – SLES solutions should be deployable to solve similar problems in different areas.

The autonomous and self-organising nature of MAS gives these techniques strong potential for creating flexible PnP solutions to the problems presented by SLES. A solution has PnP capabilities if devices can be added or removed from the system without the system itself needing to be reconfigured. PnP capabilities are key to meeting the goals of SLES, and MAS is one potential technique for achieving PnP.

1.2.3 Agent negotiation

In an MAS negotiation is the foundation for allowing the actions of the agents within the system to meet the goals of that system. This is necessary because agents are autonomous, with no knowledge of the overall desire of the system designer, and internal goals that may conflict with the goals of other agents. Agent negotiation is managed by negotiation protocols, which are the rules governing the negotiation participants, the negotiation states, and the valid actions of the negotiators (Beer et al, 1999). A negotiation object is an issue over which negotiation should be reached. MAS can have a single negotiation object, or there may be multiple factors which must be considered together. Internally to the agents the agent reasoning model is the basis by which the participants make decisions to best achieve their objectives.

1.2.4 Model predictive control

MAS can integrate with a range of control systems which can be deployed in SLES. The ADEPT demonstrator uses a type of feedback control called model predictive control (MPC). This can be used for more complex systems with multiple variables and where conventional industrial controllers are insufficient. MPCs contain use models to predict the changes in system output that result from given changes in system inputs, with the aim of reducing the effects of uncertainly on a system. Conventional MPCs sample current state of the system, and decide control actions on that basis; however state-of-the-art MPCs use forecasting techniques to better estimate the future state of the system, and the impact of control actions (Baldivieso Monasterios and Trodden, 2018).

1.2.5 Multi-agent model predictive control

The nature of both MAS and MPC presents opportunities for the combination of these technologies to provide distributed control. This combination is sometimes referred to as Multi-agent model predictive control (Negenborn et al, 2009) and has been used in the control of traffic networks, communication networks, manufacturing processes, and, of particularly relevance, power networks (Negenborn, 2007). The design basis for these control methods is to have multiple agents attempting to solve the control problem, usually by breaking the control problem down into smaller problems, thus reducing the overall computation burden, while allowing multiple solutions to be investigated simultaneously (Negenborn et al, 2009; Ferrari-Trecate et al, 2009; Hunag et al, 2015).

However, this combination of MAS and MPC was not suitable for the desired extension of the ADEPT system. Because each MPC-controlled unit was to act independently, one control problem did not exist for the whole system. Thus, a different form of inter-microgrid interactions was required. In this case agent-based control of energy trading was the most promising.

1.2.6 Energy trading between microgrids

Energy trading is potentially a particularly valuable form of inter-microgrid interactions. Previous research in this area has identified potentially significant financial savings from allowing microgrids to trade electricity (Wang and Huang, 2018), rather than importing and exporting using the grid. This has included microgrids controlled by a common operator (Fathi and Bevrani, 2013b; Fathi and Bevrani, 2013a) microgrids co-ordinated by a hierarchical structure (Asimakopoulou et al, 2013; Wang et al, 2015), interactions between islanded microgrids (Matamoros et al, 2012), and microgrid participation in energy auctions (Zhang et al, 2014).

Additionally, and of particular relevance, is research on the agent-based control of trading power between two microgrids with demand response, with the aim of reducing peak demand (Kumar Nunna and Doolla, 2013; Kumar Nunna and Doolla, 2012). This highlights that agent-based control of electricity trading can provide benefits to participating microgrids.

2 Case study

2.1 Implementation

2.1.1 Agents

The purpose of the MAS layer in the architecture is to increase both the functionality and flexibility of the distributed MPC control. Specifically, the desire was to allow the MPC-controlled 'ADEPT units' to interact with each other in order to co-ordinate the buying and selling of electricity between each other as much as possible, rather than using the potentially costlier solution of balancing solely using the grid.

To achieve this, three types of agent were designed. The first, the **MPC agent**, was a 'wrapper' around the MPC units, and controlled the flow of information between the units and the other agents. The second was the **Market agent**, which takes the information from the MPC units and, through an internal marketplace, balances the energy supply and demand of the units, allowing units to buy and sell energy from each other if that is more cost effective than using the grid.

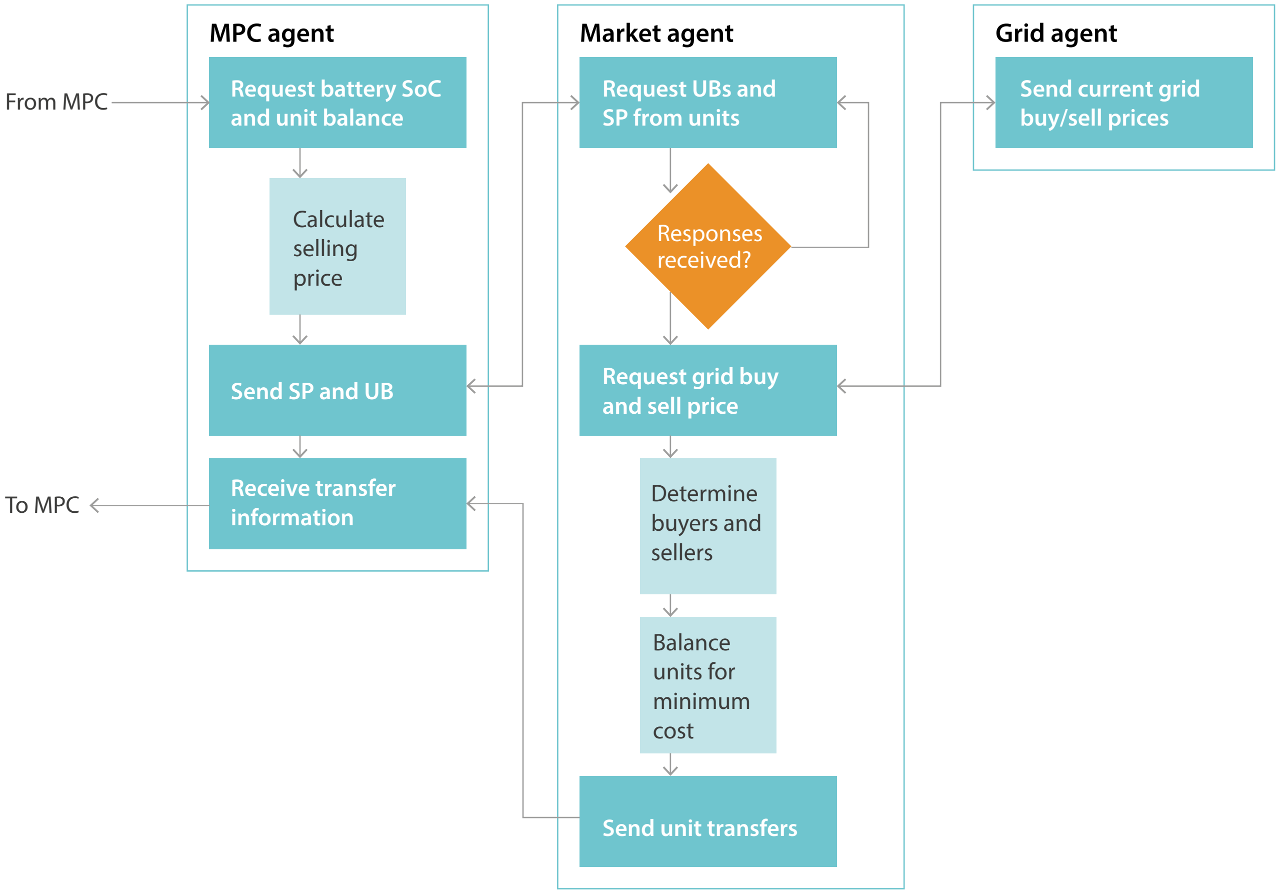

Figure 1: Agent internal and external operations

Finally, a **Grid agent** determines the current cost of buying and selling electricity from the grid,[1] and feeds this information to the market agent as required. The interactions between the agents, and the internal actions of each agent are shown in Figure 1.

Using the negotiation protocol (see appendix for more details) the Market Agent devises the optimal transfer of electricity between MPC units with the remainder of balancing performed using the grid. The required transfer for each of the MPC units is then sent to the MPC Agents which instruct the MPC Units to carry out the transfers. The grid is not considered to have any limits on import or export, so convergence is guaranteed regardless of the standing conditions of the negotiation.

1 It is assumed that all the MPC-controlled microgrids would be buying and selling electricity at the same grid prices. In reality both buying and selling would be subject to tariffs agreed with a supplier (Scott, 2016). In this case study, a steady buying price of 0.1 £/kWh was used (taken as at the lower end of available prices (Business Electricity Prices, 2020; Ofgem, 2020a)), and an export value of 0.05 £/kWh (taken as at the higher end of available prices (Ofgem, 2020b; Riley, 2020).

3 Lessons learned

3.1 Evaluation of solution

3.1.1 Financial evaluation

Initial testing of the MAS architecture was promising, showing that the use of inter-unit balancing represented a financial benefit when compared to the units running separately. An example of the final result of a round of balancing for ten units is shown in Figure 2. This demonstrated that the agent extension architecture was able to facilitate energy trading between the different units, with, at least in this example, an overall financial saving for the participants.

MPC_Unit_9 Transferred 305kWh to MPC_Unit_1 at a price of £20.7781
MPC_Unit_3 Transferred 46kWh to MPC_Unit_2 at a price of £3.3063
MPC_Unit_9 Transferred 32kWh to MPC_Unit_2 at a price of £2.18
MPC_Unit_3 Transferred 276kWh to MPC_Unit_7 at a price of £19.8375
MPC_Unit_10 Transferred 116kWh to MPC_Unit_7 at a price of £10.15
Total cost of balancing was £56.2519
Cost of balancing using only the grid would be £77.50
Total savings from inter-unit balancing are £21.2481
Total earnings if electricity only sold to the grid would be £87.40
Total earnings from inter-unit balancing was £104.9019
Total increased earnings was £17.5019

Figure 2: Example of agent negotiation results.

The system was tested further, with Figure 3 showing the impact of the agent negotiation framework over a random run of 1000 attempts for different numbers of MPC units, from two up to 10.

This suggested that there was a significant financial benefit from using the framework. This was true even when only two MPC units were involved, with this number increasing as the number of MPC units available increased. Units that were selling electricity saw an average increased income of around 15%–25% depending on the number of MPC units in the system, while units which where buying were able to do so at 10%–15% less cost than using the grid, again depending on the number of MPC units in the system.

This confirms that, over a longer period of time the MAS/MPC framework was able to facilitate energy trading to the benefit of each participating microgrid.

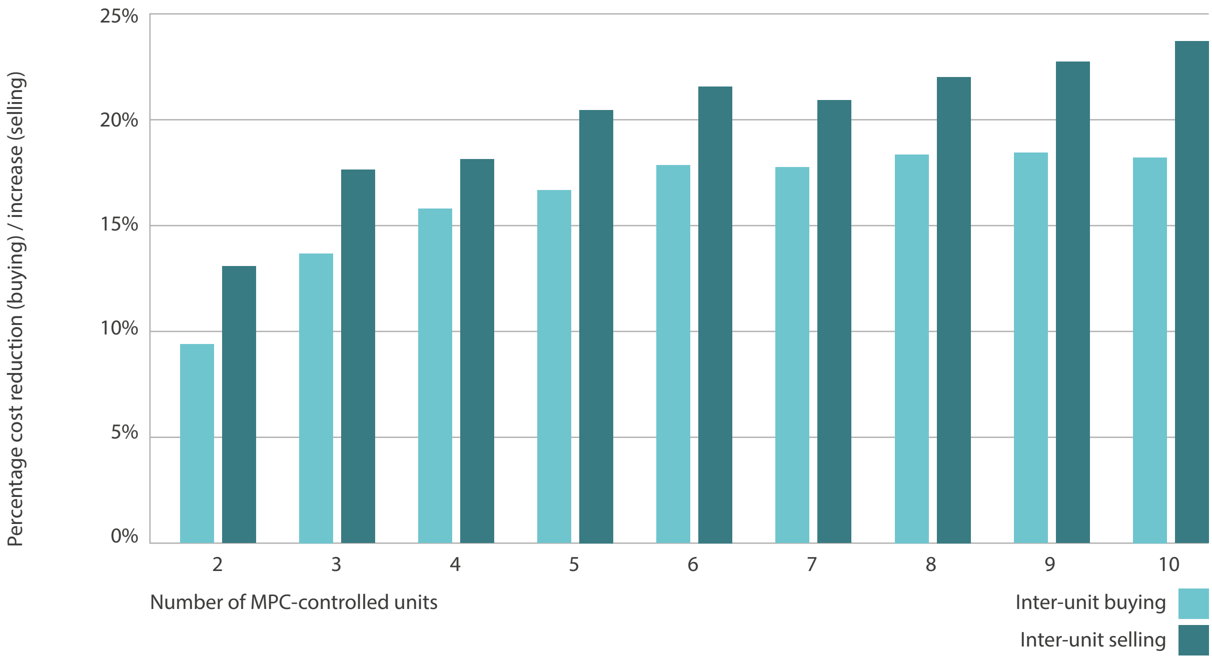

Figure 3: Impact of use of agent negotiation protocol compared with grid balancing

3.1.2 Performance evaluation

Table 1 shows the performance of the agent negotiation framework, over a second random run of 1000 for different numbers of MPCs, again from two to ten.

The performance is evaluated by the number of rounds before convergence, and the average utility value given by Equation 1 (see Appendix) for each end solution. Convergence occurred in each of the scenarios, as expected, with this being achieved after a greater number of rounds, when more agents were involved.

However, the average utility also increased with the number of agents, as there were a greater number of solutions available, and thus agents were able to better maximise their own utility.

Table 1:	Performance of agent negotiation with different number of agents			
Number of MPCs	Number of rounds		Average utility	
	Mean	SD	Mean	SD
2	1.257	0.786	0.750	0.326
3	2.037	1.026	0.747	0.306
4	2.916	1.176	0.785	0.247
5	3.679	1.392	0.796	0.244
6	4.561	1.487	0.822	0.219
7	5.519	1.552	0.835	0.193
8	6.452	1.575	0.841	0.189
9	7.290	1.808	0.866	0.164
10	8.101	1.773	0.879	0.147

3.2 Conclusions and recommendations

Overall the testing results are promising; multi-agent systems were found to be a good fit for the implementation of SLES functionality.

The agent negotiation framework showed that the application of existing technologies and techniques to an existing smart grid demonstrator successfully allowed the demonstrator to better achieve the aims of an SLES.

Flexibility was demonstrated as additional functionalities were added to an existing system.

Scalability was shown because the deployment and testing of multiple units was possible without the whole system requiring reconfiguration. This was also evident from the finding that adding more units led to improved outcomes.

The wrappers that were designed are also reusable and would allow for other MPC controllers to take part in electricity trading, and with some modification could be used to allow microgrids using different control techniques to take part as well. The location of the units did not matter, so deployment would be possible regardless of location.

While technological limitations are often cited as a barrier to SLES, existing, mature, technologies like MAS can allow for PnP capabilities to be added to existing systems.

A more universal agent wrapper would be possible if it were known in advance which data structures and ontologies that a given system would utilise. It is therefore a recommendation that common data structures and ontologies be considered in SLES design to facilitate true PnP capabilities.

Appendix: Problem specification

1 Overview

The purpose of the MAS layer in the architecture is to increase both the functionality and flexibility of the distributed MPC control; specifically, the desire was to allow the MPC-controlled 'ADEPT units' to interact with each other.

For an MAS solution this required wrapping the MPCs within agents to control the flow of information between the MPCs themselves and the devices which they control, as well as other agents within the system. A market agent would be required which had access to both information about the current prices of purchasing and selling electricity using the wider grid.

The cost of purchasing electricity from the grid, as well as information about the MPC unit batteries could be then used to update the cost function used by the MPC to make control decisions.

Under normal circumstances the MPCs inform each other of control actions they intend to make, but with the addition of the agent wrapper this mere informing of control actions can be replaced with negotiation of control actions between MPCs to allow for multiple MPCs to provide balancing functions to one another.

An overview of the proposed agent layer for this architecture is shown in Figure 4.

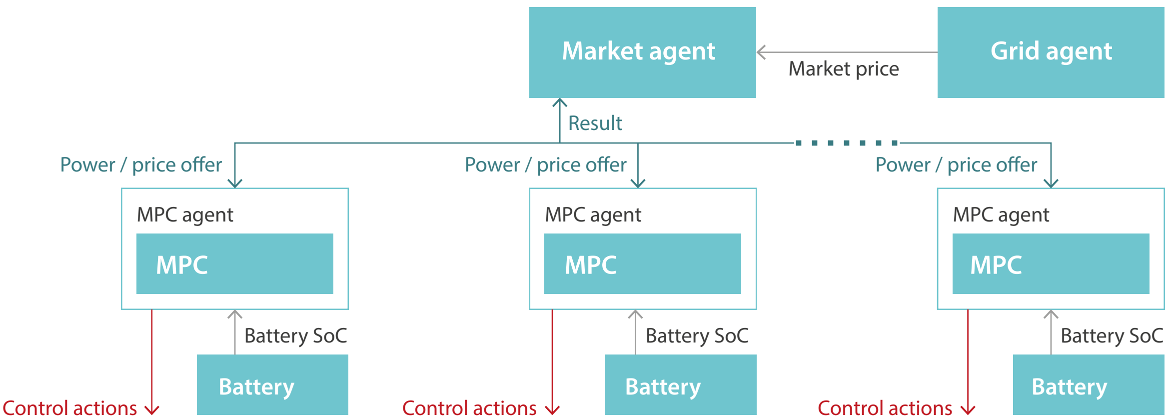

Figure 4: Multi agent system layer of extension architecture.

2 Agent interactions

Two types of agent interactions were required for the architecture in Figure 4, the first was the simple exchanging of information, which included interactions between the Grid Agent and the Market Agents.

The second was the negotiation between the MPC agents, to be performed through the broker of the Market Agent. This required the sending of the following information:

- The MPC unit's power (surplus or deficit)
- The MPC unit's battery state of charge
- The MPC unit's price offer for import (if buying)
- The MPC unit's price offer for export (if selling)
- The Market agent's balancing solution
- The MPC's acceptance or rejection of the solution

3 Negotiation requirements

The negotiation protocol required for the architecture in Figure 4 would be consensus-based, with the one agent acting as a broker, and receiving offers from the other agents, including one with information about the available prices for buying and selling from wider grid.

The wider grid was considered to have an infinite capacity for buying and selling electricity.

The aims of the negotiation would therefore be:

- To minimise the amount of energy sold to the grid
- To minimise the amount of energy bought from the grid
- To maximise the cost benefit to each of the participants

The negotiation framework would also need to consider the battery state of charge, with the desire being that units with a lower battery state of charge would be more likely to accept offers that were higher, and units with a higher battery state of charge would be more likely to offer lower prices.

4 Negotiation protocol

The design of the negotiation protocol used by the Market Agent can be summarised as in Equation 1, showing the negotiation aims of minimising both the energy imported to and exported from the grid in order to minimise overall cost of balancing the MPC units.

$$S_d = min(G_i), \qquad S_g = min(G_e)$$

$$S_d = \min\left(\sum_{j=1}^{n} d_j - \sum_{j=1}^{n} d_j(1 - SoC_j)G_{bp}\right), \quad S_g = \min\left(\sum_{j=1}^{n} g_j - \sum_{j=1}^{n} g_j(1 - SoC_j)G_{sp}\right)$$

Equation 1: Negotiation priorities for MPC balancing protocol.

Where:

- S_d is the solution for the MPC units which have an excess of demand and need to import.
- S_g is the solution for the MPC units which have an excess of generation and need to export.
- G_i is the amount of electricity to be imported from the grid.
- G_e is the amount of electricity to be exported to the grid.
- d_j is the amount of excess demand for MPC unit, *i*, (received from MPC Agent, *i*).
- g_i is the amount of excess generation for MPC unit, *i*, (received from MPC Agent, *i*).
- SoC_i is the state of charge of the battery for MPC unit, *I* (received from MPC Agent, *i*).
- G_{bp} is the buying price for importing electricity from the grid (received from the Grid Agent).
- G_{sp} is the selling price for exporting electricity to the grid (received from the Grid Agent).

Using the negotiation protocol the Market Agent devises the optimal transfer of electricity between MPC units with the remainder of balancing performed using the grid, the required transfer for each of the MPC units is then sent to the MPC Agents which instruct the MPC Units to carry out the transfers. The grid is not considered to have any limits on import or export, so convergence is guaranteed regardless of the standing conditions of the negotiation.

5 Integration

The agents as described above were originally designed and tested using Smart Python Agent Development Environment (SPADE) and were integrated into the MPC controller functions which were created using MATLAB Simulink. Due to limitations involved in integrating SPADE with MATLAB, the agents were recreated in Java Agent DEvelopment framework (JADE).This allowed for easier integration using the MACSimJX tool, which integrates JADE with Simulink. This will also allow for the testing of different negotiation strategies and protocols.

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EnergyREV was established in 2018 (December) under the UK's Industrial Strategy Challenge Fund Prospering from the Energy Revolution programme. It brings together a team of over 50 people across 22 UK universities to help drive forward research and innovation in Smart Local Energy Systems.

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