Agent-Based Appliance Scheduling for Energy Management in Industry 4.0

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Abstract. With the growing concerns regarding energy consumption, companies and industries worldwide are looking for ways to reduce their costs and carbon footprint linked to energy usage. The rising cost of energy makes energy saving and optimisation a real stake for businesses which have started to implement more intelligent energy management techniques to achieve a reduction of costs. As industries migrate towards more renewable energy sources and more sustainable consumption models, decentralised energy infrastructure is required where actors can manage and monetise energy capabilities.

In fish processing industries, energy is utilised to operate a range of cold rooms and freer units to store and process fish. Modelling thermal loads, appliance scheduling and integration of renewable energy represent key aspects in such industries. To enable the transition towards Industry 4.0 and to efficiently optimise energy in fish industries, multi-agent systems can provide the mechanisms for managing energy consumption and production with standalone entities that can interact and exchange energy with a view of achieving more flexible and informed energy use.

In this paper, we propose a multi-agent coordination framework for managing energy in the fish processing industry. We demonstrate how agents can be devised to model appliances and buildings and to support the formation of smart energy clusters. We validate our research based on a real use-case scenario in Milford Haven port in South Wales by showing how multi-agent systems can be implemented and tested for a real fish industrial site.

Keywords: Multi-agent systems · Appliance scheduling · Energy management · Cost · Smart industries

1 Introduction

With the emergence of distributed energy technologies for smart industries, it has become possible to manage energy more effectively based on the variation of energy profiles and mixes of energy network generation. The democratisation of the energy markets and the adoption of new consumption and production models stimulate urban and rural clusters to engage more actively in new smart grid economies. Developing more informed energy practices using intelligent energy management techniques represents a method to enable users to monitor energy and to participate in a market of energy services actively. Fish industries are high consumers of energy with multiple energy-intensive appliances need to process different quantities of fish where the energy load is allocated to cold rooms and freezer units. To respond to the growing concerns related to energy use in the fish industry, a smart industry model can be implemented as a mean to help fish ports to support self-adaptability, autonomy and more informed use of energy resources. Fish processing sites usually have a cluster of buildings where each building has a set of high energy consuming appliances which need to be scheduled in relation to a fish processing operation demand [1,2].

Multi-agent systems have been proven as efficient solutions for managing energy, processes and operations across industries. Multi-agent systems pose the required autonomics and self-learning capabilities, enabling a wide range of techniques, algorithms and learning strategies needed in decentralised energy systems [3]. As energy actors are dynamic and present a range of key attributes in relation to energy profiles, demand and supply, agents can be efficiently used to coordinate such an ensemble of energy actors in accordance to an Industry 4.0 vision greatly leading to more informed use of energy and reduction of the carbon emissions [4–6]. Multi-agent systems can provide the required level of intelligence for devising smart factories, in the Industry 4.0 mission to integrate products, components and production machines and to change their behaviour accordingly by storing knowledge gained from experience [7].

In this paper, we propose a multi-agent framework for appliance scheduling in fish processing industries to achieve more decentralised and effective energy management in such industries. We present the multi-agent framework with agent properties and objectives for buildings, appliances and site entities alongside the required interaction for energy exchange and coordination. The solution is validated in the context of the Milford Port in South Wales based on which different energy management scenarios have been devised. The remainder of the paper is as follows: The related work on multi-agents for energy management is presented in Sect. 2. In Sect. 3 we present our multi-agent architecture. In Sect. 4 we describe the experimental setup for the evaluation followed by the results reported in Sect. 4. We conclude our work in Sect. 5.

2 Background and Motivation Case Study

Fish processing industries are adopting new distributed energy management solutions to achieve cost reduction while satisfying the energy demand of the fish processing units. Energy use for fish processing industries can be scheduled for direct use, such as lighting systems, heating and box washing machines or indirectly by converting the power to another form of energy, such as cooling cycles, freezing and industry equipment. To efficiently manage energy in fish industries, multi-agent applications can be used to achieve a higher order of "smartness" in energy management as reported in previous works [8–10].

To model such phenomenons in energy networks, agents can use negotiations to coordinate energy sharing and exchange to meet the demanded load of the consumption units while maintaining a level of autonomy in the site. Research studies focus more on large-scale systems where energy is consumed traditionally from the national grid without an in-depth exploration of renewable energy solutions [11,12]. Energy networks with multi-agent systems are also viewed as efficacious alternatives solutions for coordinating large industrial sites with an increasing energy load [13–15].

Milford Haven is the largest energy port in the United Kingdom and is the largest supplier of oil and gas with a capacity to supply about 30% of the UK gas demand. The port operates a fish processing industrial business that conserves and delivers vast quantities of fish to other factories and supermarkets in the UK and abroad. The principal objective of the port is to reduce energy consumption and CO_2 emissions through the implementation of a smart industry solution that can efficiently optimise energy generation and consumption. Packaway building is the main building in the port and includes several energy consuming appliances: an ice machine, a cold storage room, a box washer, lighting systems and meters. A quantity of fish is stored every day in the cold room refrigerating unit that is kept at $-5\,^{\circ}$C throughout the night and day to preserve the fish. The ice flake produces the required quantity of ice for fish refrigeration, whereas the box washing machine is activated to clean the boxes where the fish is stored. Packaway has installed a PV system on the building's roof with 50 kW panels which serve the building with a daily energy supply.

Scheduling can allow the appliances to be used at the most advantageous time of the day, and to be scheduled based on optimised intervals in alignment with objectives related to energy optimisation and carbon emission. Using multi-agents, we implement a scheduling framework for the Packaway building that can be used to manage energy consumption in the building throughout the day.

3 Multi-layer Agent-Based Simulation Framework

We consider a set of agents $A = \{a_1, a_2, a_3, .., , a_n\}$, where each a_i represents a production or consumption unit within the Packaway building, such as ice-flake, cold-room, box washer and lighting. Each agent a_i also has a set of properties such as schedule, capacity or frequency and a set of constraints such as minimum running time and required start time. Each appliance within the Packaway building has an associated appliance agent a_i whereas the solar panel set-up is implemented by a single solar panel agent. An energy provider agent acts as the grid energy provider in the physical building (see Fig. 1). Each appliance agent has a daily demand for energy with a predefined constraint to consume the amount of energy at the lowest possible price and emitting as little carbon dioxide as possible. To achieve this, the agent can schedule its consumption in one of the four time slots of the day, consuming either solar energy produced by the solar panels of the building or energy provided from the national grid. The solar panel agent simulates the energy production of the solar panels installed on the building and informs the main building agent regularly with the amounts of energy available for appliance consumption. The interaction between the different agents is presented in Fig. 1.

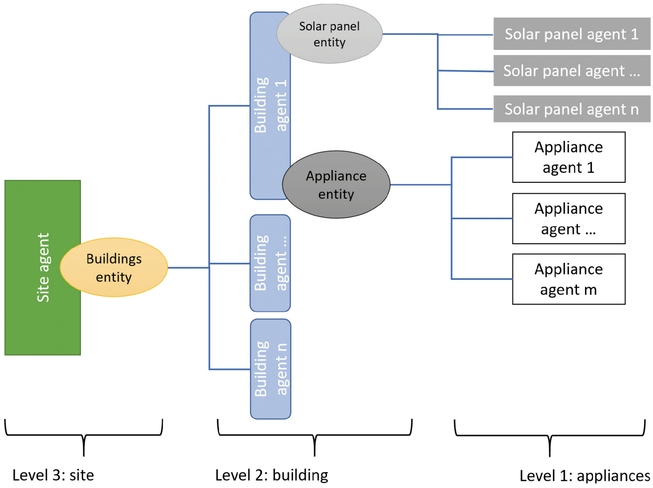

Fig. 1. The multi-agent framework with corresponding layers.

The appliance agents and solar panel agents compose the first level of the multi-agent framework. A building agent is programmed to consume the sum of all its appliance agents' consumption and produces the sum of all its solar panel agents' production. From one level of agents to the next, some of the properties are the same, such as production or consumption, but have slightly different roles and different methods to perform a required set of tasks. The multi-layer architecture also means that an agent decision can have an impact on agents from a different layer. A more detailed presentation of the multi-agent layer is presented in the following subsection.

3.1 Layers of Agents

In this section, the specifications of each layer of agents will be explained and detailed. This will provide a greater understanding of the modelling framework and the policies of interaction between different layers and agents.
The appliances layer is formed of five types of agents. There is one agent designed for each type of physical appliance in the Packaway building and one for the solar panel system. We implement agents specific for these types: 'coldroom' type, an 'iceflake' type, a 'boxwash' type and a 'light' type as well as a 'PVpanel' type where each type matches to a class in the overall implementation. Each agent matches to a physical appliance or a solar panel with a key differentiation between appliance agents and solar panel agents based on energy usage and consumption patterns.

– Static: ID, Capacity, Daily Usage
– Theoretical (dynamic): Schedules, Status
– Practical (dynamic): Consumption, Cost, CO2 emission, Log

Each appliance agent has a set of properties and a set of methods that simulate the behavior of its physical entity (appliance) and enable the interaction of the appliance with other entities in the building with decisions made on daily basis.

The buildings layer – is formed of one type of agent which acts as a manager for the appliance agents and solar panel agents. Each building agent manages a set of appliances and solar panel agents and has identifiers such as ID, weekly usage, appliances, solar panel and grid energy provider whereas the decision-making properties are related to status, production and consumption schedules, prices and CO_2 emission of solar and grid energy. There are three types of properties for a building agent; static, theoretical and practical, as presented below:

– Static: ID, Appliances, Week-usage, Solar panel, Grid provider
– Theoretical: Week-schedule, Status, Solar-schedule, Prices, CO_2
– Practical: Consumption, Production, Cost, CO2 emission, Week-stats, Logs

The building agent has properties that contain a list of appliance level agents and can be both consumers and producers of energy where the consumption consists of the sum of consumption for all the appliances in the building.

A building agent has methods to perform various actions from calculation of bills with appliances and solar panel to information retrieval and decision making and has a set of key methods for collecting information from all the appliances, solar panels and energy provider agents. This permits the building agent to update the prices and CO_2 properties and to make decisions in relation to the optimum operation schedule of an appliance (time to start, operating interval, etc).

The site layer – contains higher level agents that coordinate building agents based on consumption and production objectives. Each site agent is programmed to orchestrate information exchange between the building with a wider objective of sharing energy efficiently within the local cluster.

The decisions of the site agent are similar to an appliance or building agents but with a greater impact on the building agents and associated appliance and solar panel agents. The site agent also saves up site data in its log over which a set of methods operate to take decisions for coordinating lower level agents and to model behaviours throughout the simulation.

4 Evaluation and Results

The multi-agent framework is implemented in Matlab, where each agent is a class with functions and attributes. The multi-agent framework has been calibrated with data from the real site, where each agent has a production or consumption capacity, a set of behaviors and associated constraints. The overall simulation process is organised in three rounds starting with the initialisation of agents, then the execution of the process and lastly the optimisation of appliance schedules.

Step 1: Initialization – is the phase that sets the parameters and configures the environment for the experiments with two operations (i) agent creation and calibration with real site data including appliance agents and solar panel agents and (ii) a message board mechanism enabled to circulate information about the simulation such as prices and the CO_2 emission characteristics.

Step 2: Execution – is the main part of the program and contains the instructions to run the simulation such as the number of weeks, agents and constraints. The appliance agents work on a day time interval divided into four periods, while the building agents work on a week interval divided into several days.

Step 3: Finalization – is the phase that saves the relevant information for all the building agents, all the appliance agents and solar panel agents in a log aimed at capturing the amount of energy that agents have produced or consumed throughout the simulation.

In the experiments, we seek to optimise energy consumption and production using building level agents and appliance level agents designed and implemented based on the observations from data of the Packaway building. We have devised three scenarios where different input parameters are varied in order to observe how different factors simulated with multi-agent behaviours can impact and optimise energy production and consumption and also impacting CO_2 emissions and energy costs in fish ports. The configuration is using a default energy type, a production capacity, a price and a CO_2 emission level such as: (i) solar energy with a 2.5 kWh/day capacity, a 0.10 £/kWh price, a 32 g/kWh emission level and (ii) grid energy type with infinite capacity, 0.15 £/kWh and 66 g/kWh.

Scenario 1: Four Appliances Scheduling Strategy

This scenario investigates a default energy management plan for the Packaway building where all four appliances are optimally scheduled to support the main fish operation with an objective to consume minimum energy consumption. The scheduling mechanism for the appliance agents is based on daily usage and reflects the physical building consumption and production as retrieved from the site investigations. The overall objective of the agents is to collaborate based on a shared scheduling plan, where all the appliance agents schedules are optimised based on the time of the day, demand of fish, demand of ice and energy consumption. The experiment is configured with adequate appliance capacities and usage, as presented below, in order to assess impact on production, consumption, cost and CO_2 emissions. The configuration of the experiment is (i) Cold room with 10 kW production capacity and 70 kWh/day consumption (ii) Box wash with 50 kW capacity and 1 kWh/day, (iii) Ice flake with 32 kW capacity and 50 kWh/day and (iv) light with 0.5 kW capacity and 1 kWh/day.

As presented in Fig. 2, the experiment aims to explore the performance of the building when appliances operate at different capacities and calibration comparing to real site observations. Theoretically, the building should consume 122 kWh

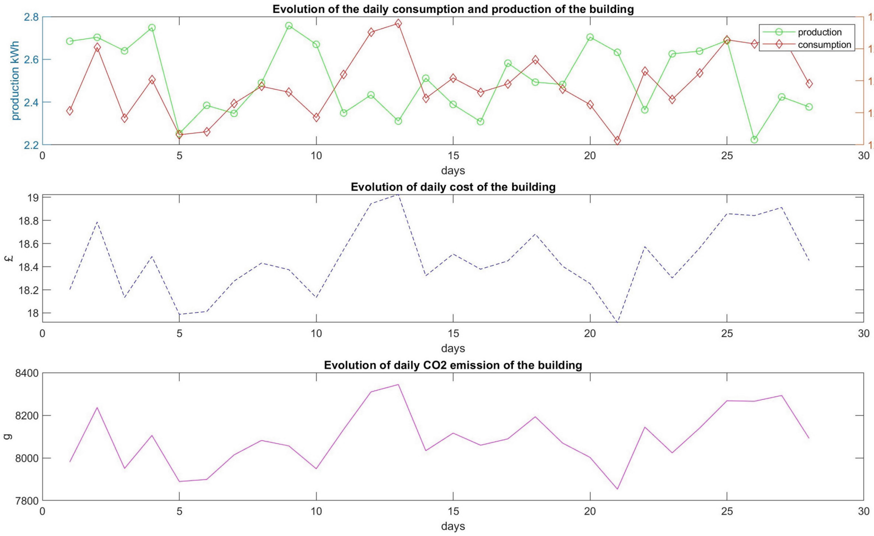

Fig. 2. Energy consumption, production, cost and CO_2 emissions with four appliances.

of energy every day based on the site observations. As we can see from Fig. 2, the daily consumption of the building varies between 120 and 128 kWh. This is a variation of less than 5% of the expected value which demonstrates that the multi-agent framework has the ability to simulate and model any building scenario with high precision and the multi-agent scheduling strategy is beneficial in terms of energy use and cost. In the scenario where four appliances operate at full capacity, the cost of the consumed energy, as well as the amount of CO_2 emitted, are proportional to the energy consumed. This is because the agent function that models energy consumption at the building level is linear as derived from historical building consumption data.

Scenario 2: Scheduling Appliances When Demand Increases

This scenario is meant to test the influence of the demand of energy on the appliances in a day interval where all four of the appliances are in operation. To test the impact of the scenario we have increased the daily energy allowed consumption of the appliances by 25%. The configuration of the experiment is (i) Cold room with 10 kW capacity and 88 kWh/day consumption (ii) Box wash with 50 kW capacity and 1.25 kWh/day, (iii) Ice flake with 32 kW capacity and 63 kWh/day and (iv) light with 0.5 kW capacity and 1.25 kWh/day.

Theoretically, the appliances should consume 153,5 kWh every day and according to the results reported in Fig. 3, energy consumption fluctuates between 150 and 165 kWh. This is a variation of nearly 8% around the desired value showing that when more energy is required for the appliance agents, the scheduling is constrained and less optimization strategies can be implemented to impact the cost and CO_2 emissions. Another general observation on the multi-agent framework is that the simulation loses in accuracy when the amounts of

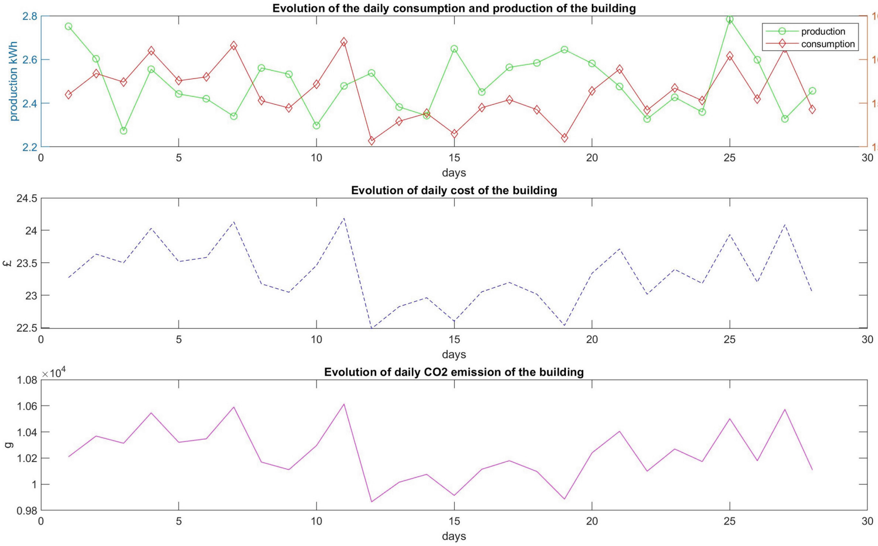

Fig. 3. Energy consumption, production, cost and CO_2 with increased demand.

energy increases which can bring additional constraints when energy needs to be optimally managed at a large scale.

5 Conclusion

In this paper, we present how agent-based appliance scheduling can be used to support more efficient energy management in fish industries. We consider that multi-agents can greatly support energy coordination in energy-intensive industries with great potential to optimise cost and reduce carbon emissions. Through experiments, we explore different appliance scheduling techniques in the attempt to devise a multi-agent based decision support system for energy site managers that is fully aligned with the latest carbon reduction governmental strategies. Fish ports need to exploit the vast potential of data-driven techniques for increasing the informational level in the ports and for enabling a more intelligent decision process as part of the Industry 4.0 transition.

The modeling of different levels of complexity in fish industries can lead to a more holistic understanding of the intrinsic energy processes and help in identifying areas of improvements. We have primarily focused on decarbonising ports and proposed a more economical strategy for managing energy and operations in fish processing industries using multi-agent systems as a mean to pave the way towards implementation of a smart industry model.

We demonstrate how a multi-agent framework can also optimise cost with energy in direct relation with the number of appliances in operation, production units, and building properties. We have also emphasised the essential techniques that can reduce consumption and make more informed use of energy produced in a fish site which can be utilized when developing the smart grid and corresponding business models.

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