Engineering Applications of Artificial Intelligence 127 (2024) 107198

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

An agent-based approach for energy-efficient sensor networks in logistics

Jan Kaiser[a,*], Marco Pérez Hernández[b], Victor Kaupe[c], Philip Kurrek[d], Duncan McFarlane[a]

[a] University of Cambridge, 17 Charles Babbage Rd, Cambridge CB3 0FS, United Kingdom
[b] University of the West of England, Coldharbour Ln, Bristol BS16 1QY, United Kingdom
[c] BASF Coatings GmbH, Glasuritstraße 1, 48165 Münster, Germany
[d] University of Plymouth, Drake Circus, Plymouth PL4 8AA, United Kingdom

ARTICLE INFO

Keywords:
Multi-agent system
Sensor networks
Energy-efficient
Monitoring
Logistics
Decision making

ABSTRACT

As part of the fourth industrial revolution, logistics processes are augmented with connected information systems to improve their reliability and sustainability. Above all, customers can analyse process data obtained from the networked logistics operations to reduce costs and increase margins. The logistics of managing liquid goods is particularly challenging due to the strict transport temperature requirements involving monitoring via sensors attached to containers. However, these sensors transmit much redundant information that, at times, does not provide additional value to the customer, while consuming the limited energy stored in the sensor batteries. This paper aims to explore and study alternative approaches for location tracking and state monitoring in the context of liquid goods logistics. This problem is addressed by using a combination of data-driven sensing and agent-based modelling techniques. The simulation results show that the longest life span of batteries is achieved when most sensors are put into sleep mode yielding an increase of $\times 21.7$ and $\times 3.7$ for two typical routing scenarios. However, to allow for situations in which high quality sensor data is required to make decisions, agents need to be made aware of the life cycle phase of individual containers. Key contributions include (1) an agent-based approach for modelling the dynamics of liquid goods logistics to enable monitoring and detect inefficiencies (2) the development and analysis of three sensor usage strategies for reducing the energy consumption, and (3) an evaluation of the trade-offs between energy consumption and location tracking precision for timely decision making in resource constrained monitoring systems.

1. Introduction

The fourth industrial revolution has transformed enterprises. Emerging digital technologies are used to integrate business and manufacturing processes in order to cope with rapid changes in customer demand and production alterations (Rojko, 2017). While the majority of digitalisation endeavours focus on manufacturing, it is crucial to also augment logistics processes with connected information systems to enhance their reliability and sustainability (Kayikci, 2018). In particular, companies can analyse data from interconnected logistics operations to provide customers with an efficient and transparent service delivery, reduce costs and increase margins. A key driver for such logistics processes is the Internet of Things (IoT), which enables the cooperation and collaboration among actors along the value chain of the enterprise (Atzori et al., 2010).

An industrial application of such an augmented logistics process is for the monitoring of liquid goods. In this case, sensors are attached to intermediate bulk containers (IBCs). The objective is to use this information to improve customer service and rapidly react to disruptions that occur during transport. However, in situations where IBCs are stored or moved in bulk the sensors transmit much redundant information that does not provide any additional value to the customer. Likewise, there is a need to reduce the energy consumption of sensors to extend the battery life span and decrease the maintenance costs of the system.

To address this issue, a variety of possible control and coordination approaches can be used, most of them fall somewhere on a spectrum between *centralised* and *distributed* (Morstyn et al., 2018). Ad-hoc sensor networks, where the sensor location is unknown a priori, are generally supervised by a centralised control strategy (Cardei and Wu, 2006). The energy consumption of sensors is reduced by scheduling the node activity and minimising the sensing and communication range while meeting the overall sensing objective. In contrast, agents enable an inherently distributed control. Agents are computing elements capable of interacting with one another (Wooldridge and Jennings, 1995). Besides the cooperation, coordination and negotiation with others, agents are capable of acting autonomously. That is, they can make decisions independent from external interventions and are able to work

* Corresponding author.
E-mail address: jk823@cam.ac.uk (J. Kaiser).

https://doi.org/10.1016/j.engappai.2023.107198
Received 31 October 2022; Received in revised form 3 July 2023; Accepted 21 September 2023
Available online 30 September 2023
0952-1976/© 2023 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

proactively to meet the system goals. While ad-hoc sensor networks typically rely on global scheduling rules, agents have a narrow view of the network and decisions are made in a distributed manner.

The main objective of this paper is to explore different strategies for an energy-efficient collection of relevant logistics monitoring data of liquid goods. In essence, this paper is concerned with the *value of information* for this particular use case and aims to determine how to minimise the information needed. Therefore, to distinguish between relevant and redundant data, the sensing needs to be data-driven, and to meet the characteristics of the considered logistics monitoring application, a distributed agent-based approach is suitable. We review alternative approaches that are able to model the system characteristics, investigate strategies that can be adopted to improve the energy inefficiencies of the system and analyse the effect of agents on the capability to make decisions by evaluating the energy savings and information loss for two typical routing scenarios. Additionally, we validate the results by simulating three cases of disruptions that typically occur during transportation. The key contributions of this paper include (1) an agent-based approach for modelling the dynamics of liquid goods logistics to enable monitoring and detect inefficiencies, (2) the identification, implementation and systematic analysis of three strategies for reducing the energy consumption of tracking sensors for liquid goods logistics, and (3) an evaluation of the trade-offs between energy consumption and location tracking precision for timely decision making in resource constrained liquid good logistics monitoring systems.

The paper is structured as follows. In Section 2, we review studies presented in the literature that are focused on energy-efficient sensor networks and agent-based approaches for monitoring, and perform a critical analysis of their feasibility for the IBC monitoring application. In Section 3 we introduce the industrial monitoring application that serves as a basis for this study. Section 4 proposes the agent model including main algorithms and metrics to compare and evaluate the different energy efficiency strategies. Section 5 describes the assumptions and implementation of the simulation conducted in this study. Then, Section 6 evaluates the agent strategies and presents three cases of disruptions to validate the evaluation results. In Section 7, we describe the limitations of this study and discuss lessons learnt of applying the agent model to the industrial use case. Finally, conclusions are drawn.

2. Related work

Sensor networks have been deployed in a variety of industrial applications, including logistics, manufacturing and telecommunication. Much work has been done on reducing the energy consumption of sensors through route optimisation and developing control algorithms for an efficient message dissemination. However, one of the limitations of existing approaches includes the need for analysing the capabilities of agents to reduce the energy consumption of sensor networks in logistics, and the need for studying the trade-off between energy consumption and decision-making capabilities as a result from missing information in resource constraint environments. In this section we outline research gaps in the study of agent-based control for monitoring containers and describe the focus of this study. We begin by presenting existing approaches for increasing the energy efficiency of sensor networks, which is followed by an overview of agent-based and IoT-enabled monitoring applications. Apart from that, we discuss studies on the value of monitoring information for manufacturing and logistics. Finally, we perform a critical analysis of the feasibility of existing energy efficiency approaches presented in the literature to be applied to the considered IBC monitoring application.

2.1. Energy efficiency for sensor networks

The sensors in an ad-hoc sensor network are typically resource constrained and are characterised by a dynamic network topology, an event-driven or on-demand type of interaction, and an improved positioning and fault tolerance since usually more sensors are deployed than required (Cardei and Wu, 2006). There are a number of approaches that deal with minimising the energy consumption in such networks: first, both Slijepcevic and Potkonjak (2001) and Oh et al. (2005) rely on a centralised control mechanism. The former divides sensors into mutually exclusive sets, where one set is active at any time for a fixed interval. The latter forms sensor clusters and assigns a manager node for each cluster, which transmits data collected from the clustered sensors via the shortest node path. On the other hand, Tian and Georganas (2002) propose a distributed control approach, in which the sensor node activity is scheduled based on varying sensing ranges. Furthermore, Intanagonwiwat et al. (2003) study directed diffusion for wireless sensor networks (WSNs). A subset of paths between sink and source is reinforced to transmit data in a shorter interval. Fissaoui et al. (2017) employ mobile agents that migrate between different clusters of sensor nodes and gather data. To increase energy efficiency, the agents only travel to and gather data from the cluster heads. Finally, Din et al. (2019) present a multi-layer clustering approach to select a forwarding sensor node. Each cluster head node includes a routing table, which is used to switch roles among sensor nodes in the cluster.

Apart from that, several studies focus on optimising routing in WSNs to reduce their energy consumption. For example, Logambigai et al. (2018) propose an energy-efficient grid-based routing algorithm, which is based on fuzzy rules to reduce the number of hops and find the optimal route. Selvi et al. (2021) propose a hierarchical clustering algorithm based on gravitational force. This approach uses the concept of force attraction, which allows each node to move depending on its distance and direction. If two nodes come closer, they from a cluster. To reduce energy consumption, routing is performed through the cluster heads, which are determined via fuzzy logic and relevant metrics, such as distance and residual energy.

Additionally, there are two key challenges in WSNs that have an indirect effect on its energy efficiency, namely ensuring a full coverage of the sensing area, and enabling a reliable and fast message dissemination. There are several studies which address these two issues. For example, Cao et al. (2020) propose a robust distance-based relay node selection in vehicular networks. The relay node is selected by maximising the average speed of the message dissemination for different vehicle densities. Kumar et al. (2021) propose to reduce redundant data dissemination through a combination of k-means and unequal fuzzy clustering. Apart from that, Wang et al. (2018) address the coverage control problem in WSNs through a particle swarm optimisation. The control algorithm partitions the network into grids, and adjusts the sensing radius of the nodes based on the coverage rate and energy consumption of each grid.

2.2. Agent-based approaches for monitoring

Agents have been adopted in a wide variety of monitoring applications. In the domain of logistics, Jedermann et al. (2006) leverage wireless sensors in combination with mobile software agents, which preprocess the data and transmit only relevant information, in order to track the changes of good quality along the supply chain. Chow et al. (2007) use agents and RFID to monitor the process status of warehouse operations, Hribernik et al. (2010) rely on agents to control and supervise the material flow in transport logistics. For manufacturing, Rocha et al. (2015) propose an agent-based architecture that is able to adapt to changes in the network topology. Each manufacturing resource is monitored by an agent that transfers data to cloud agents for analysis. In the context of environmental monitoring, Athanasiadis and Mitkas (2004) suggest to utilise agents for tracking and validating air-quality measurements from sensor arrays.

Agents can also be embedded into nodes of ad-hoc sensor networks to enhance their capabilities. Qi et al. (2001) use mobile agents to overcome network latency. They propose to improve the infrastructure to integrate relevant data into nodes of the sensor network. Apart from that, Wu et al. (2010) develop agents for a WSN of a structural health monitoring application. The authors show that agents are resilient to disturbances and reduce the amount of data sent.

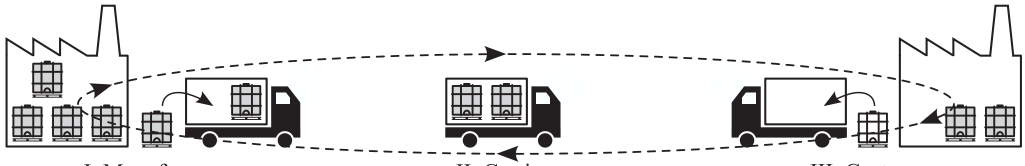


Fig. 1. The three phases of a closed IBC life cycle. At the customer, empty IBCs (white) are replaced with filled containers (grey).

2.3. IoT-enabled monitoring of containers

Along with the rise of the IoT, monitoring systems have emerged that harness the implicit connectivity of devices, specifically for monitoring containers in logistics processes. However, not many applications can be found as the increasing number of distributed embedded systems has led to an exponential growth of communication load on devices (Muhuri et al., 2019), thus yielding a challenging development of resource constrained systems. Arumugam et al. (2018) employ IoT technologies in conjunction with smart contracts to supervise assets in the supply chain, which includes monitoring containers transported via trucks. Moreover, Salah et al. (2020) propose a hardware and software system architecture for shipping containers for condition monitoring and location tracking.

2.4. The value of monitoring information

The analysis conducted in this study is further related to the research on the value of information, which aims to quantify the effect of information availability to make decisions (Russell and Norvig, 1995). A number of studies focus on quantifying the value of information for monitoring and tracking applications. Kelepouris et al. (2012) evaluate how the accuracy and timeliness of product location information across a supply chain affects decision effectiveness. Furthermore, Wong and McFarlane (2007) investigate the role of readily available product information in enhancing shelf replenishment performance. In the context of manufacturing, Parlikad and McFarlane (2007) study the impact of available product information on product recovery decisions.

2.5. Feasibility of existing energy efficiency approaches for liquid goods logistics

This study is concerned with modelling the dynamics of liquid goods logistics to detect inefficiencies and enable timely decision making. The sensors attached to the IBCs form a large-scale highly distributed network, whereby the state and location information of IBCs (i.e. nodes) change readily. Generally, there exist no approaches in the literature that consider the different situations the network nodes may encounter. For example, the end user may require different sensor information depending on the location of IBCs. Apart from that, centralised control approaches are likely to be ill-suited for the considered distributed monitoring application, since they may yield a performance bottleneck for a large number of IBCs. In this section we analyse the feasibility of existing energy-efficient WSN approaches to meet the characteristics of the IBC monitoring application. Table 1 provides an overview of the feasibility analysis.

Centralised control approaches (Slijepcevic and Potkonjak, 2001; Oh et al., 2005; Selvi et al., 2021; Wang et al., 2018) are likely to be ill-suited for the considered monitoring application, as they may yield a performance bottleneck for a large number of IBCs. In contrast to the control approaches proposed by Slijepcevic and Potkonjak (2001) as well as Oh et al. (2005), ensuring full coverage of the sensing area is unnecessary for the monitoring of IBCs, since each container is equipped with an individual sensor. The centralised gravitational force based clustering algorithm proposed by Selvi et al. (2021) may become a bottleneck for a large number of sensor nodes. The approach proposed by Wang et al. (2018) is not feasible for the considered use case, since the IBC sensor nodes are not static and using fixed-sized grids is less efficient than a distance-based clustering algorithm for the dynamic topology of IBCs. Specifically, in case where multiple IBCs are transported in bulk, the majority of sensors can be put into sleep mode, since the containers undergo similar environmental conditions, and thus, these IBCs can be clustered. A fixed-sized grid may cause a separation of such clusters, which results in more sensors remaining active and therefore a higher energy consumption. Moreover, the sensing range of IBC sensors cannot be altered. For the multi-layer clustering approach proposed by Din et al. (2019), the data gathering from IBC sensors within a cluster is not required in most situations and therefore results in unwanted energy wastage. Finally, to select appropriate relay nodes for an efficient message dissemination as suggested by Cao et al. (2020), there is not enough data available for the considered monitoring application to enable an evaluation and comparison of different message dissemination speeds for the wide range of IBC routing patterns.

On the other hand, distributed control approaches (Tian and Georganas, 2002; Intanagonwiwat et al., 2003; Fissaoui et al., 2017; Logambigai et al., 2018; Kumar et al., 2021) are more likely to satisfy the requirements of the IBC monitoring application. However, not all of them yield energy savings upon adoption. For example, the coverage-preserving node scheduling approach proposed by Tian and Georganas (2002) is not feasible since enhancing the coverage of the sensing area is unnecessary for the considered use case. Furthermore, for the directed diffusion approach proposed by Intanagonwiwat et al. (2003), the shortest path computation is not energy-efficient for dynamic topologies, since the location of nodes change readily and thus needs to be queried more often than for static topologies. The energy-aware data aggregation approach introduced by Fissaoui et al. (2017) is not feasible as well, since the itineraries of IBCs are determined based on customer orders and cannot be changed by the control algorithm. Similar to Wang et al. (2018), the use of fixed-sized grids for clustering is also suggested by Logambigai et al. (2018), which is less efficient than a distance-based clustering for the considered IBC monitoring application. Finally, the clustering algorithms and energy efficiency strategies proposed by Kumar et al. (2021) are similar to those chosen in this study and are therefore likely to yield the same results. However, these strategies are not capable of detecting the different situations IBCs encounter and they are not able to provide specific information for the end user depending on these situations.

2.6. Summary

Although there are various studies on controlling sensors in a monitoring application, existing energy efficiency approaches are not feasible for the considered large-scale highly distributed IBC monitoring system. Specifically, two main issues have not been addressed yet: first, while some studies have investigated the use of agents to support the monitoring of logistics operations, there are no attempts to examine a reduction of the energy consumption in sensor networks with dynamic topologies through the use of agents. Investigating energy consumption is important because it is a common issue of large-scale logistics and supply chain processes. Second, there is a need for studying the trade-off between energy consumption and location tracking precision of monitoring systems in resource constrained environments and its effect on the decision-making capabilities.

Table 1
Analysis of the feasibility of related energy-efficient WSN approaches for the IBC monitoring application.

Approach	Characteristics	Feasibility
Slijepcevic and Potkonjak (2001)	• Centralised control • Selection of mutually exclusive sets, whose members fully cover the sensing area • Only one set is active at any time	• Ensuring full coverage of the sensing area is unnecessary for the considered application • Ill-suited for large-scale distributed applications
Oh et al. (2005)	• Centralised control • Division of sensing areas into clusters and selection of one manager node for each cluster • Transmission of data collected from the clustered sensors via the shortest node path	• Ensuring full coverage of the sensing area is unnecessary for the considered application • Ill-suited for large-scale distributed applications
Tian and Georganas (2002)	• Distributed control • Assignment of clusters by comparing overlapping sensing areas of nodes • Scheduling of the sensor activity based on these clusters	• Ensuring full coverage of the sensing area is unnecessary for the considered application
Intanagonwiwat et al. (2003)	• Distributed data-centric control • Reinforcement of a subset of paths between sink and source to transmit data in a shorter interval	• The computation of the shortest path consumes much energy in dynamic environments, since the location of nodes changes readily and thus needs to be queried frequently
Fissaoui et al. (2017)	• Distributed control • Planning algorithm for mobile agents that migrate between sensor clusters and gather data from cluster heads	• Not applicable to the considered use case, since the itineraries of IBCs are determined based on customer orders
Din et al. (2019)	• Multi-layer clustering approach that selects a sensor transmitting the data of a cluster • A table for intra- and inter-routing is used to switch the roles among sensors in the cluster	• For the IBC monitoring application, gathering data from sensors within a cluster is unnecessary in most situations and would therefore yield unwanted energy wastage
Logambigai et al. (2018)	• Distributed control • The network is clustered into grids with a certain length with a coordinator for each grid aggregating the data of the sensors in that grid • Fuzzy rules are used to the reduce the number of hops and find the optimal route	• Equally sized grids are less efficient than clustering IBCs based on the distance between them for the considered monitoring application
Selvi et al. (2021)	• Centralised control • Gravitational force clustering, whereby the cluster heads are determined through fuzzy logic and relevant metrics, such as distance and residual energy • Routing is performed through the cluster heads	• The clustering may limit the performance of the distributed monitoring application when considering a large number of IBCs
Cao et al. (2020)	• Relay nodes are selected by maximising the average speed of the message dissemination for different vehicle densities	• There is not enough data available for the considered monitoring application to evaluate the message dissemination for the wide range of scenarios IBCs encounter
Kumar et al. (2021)	• Distributed control • Reduction of redundant data dissemination through a combination of k-means and unequal fuzzy clustering	• The clustering algorithms are similar to those chosen in this study and are thus likely to yield the same results • However, the proposed strategies are not capable of detecting the different situations IBCs encounter and providing specific information for these situations
Wang et al. (2018)	• Centralised control • Partition of the WSN into grids of a fixed size • A particle swam optimisation is performed to adjust each node's sensing radius according to the coverage rate and energy consumption of each grid	• The sensor nodes are not static for the considered use case • Using fixed-sized grids is less efficient than using a distance-based clustering algorithm for the monitoring application • The sensing range of IBC sensors cannot be altered

3. An industrial application for monitoring containers

This study revolves around a logistics process where liquid goods are transported via intermediate bulk containers (IBCs) to various original equipment manufacturers (OEM). To monitor the state of the goods as well as the environmental conditions, a sensor is attached to each IBC, which measures the fill level, temperature, acceleration and tracks the global position of the container. The sensor transmits data to the cloud following a configured approach. The main objective of this monitoring application is to improve decision making and provide visibility to customers. For instance, vehicle tracking information enables fast reactions to disruptions that may occur during transport, such as rerouting a truck to avoid a traffic jam.

3.1. IBC life cycle

During its lifetime an IBC goes through three different phases which are summarised in Fig. 1: first, the manufacturer receives a customer order and fills IBCs accordingly. Then, the containers are transported (usually via trucks) to the site of the customer. At the customer, the IBCs are being emptied and stored until moved back to the manufacturer. While this outlines a *closed life cycle*, in some cases IBCs do not return to the manufacturer. However, such *open life cycles* are not considered in this study.

While travelling, IBCs may be combined into different groups on different vehicles along the route towards their destinations. Two typical routing scenarios are depicted in Fig. 2: in the first scenario, a number of IBCs are transported from the manufacturer to customer A. They reside at the site of the customer while being emptied before they return to the manufacturer. For the second scenario, a subset of IBCs are located at customer B and C, which both require replenishment. A truck ships a number of full IBCs from the manufacturer to customer B, unloads the full IBCs and loads the empty containers prior to driving to customer C. At customer C the empty IBCs are replaced with filled containers before the truck returns to the manufacturer. Many other possible routing scenarios also exist. The key issue is that the set of IBCs on any one vehicle is often changing.

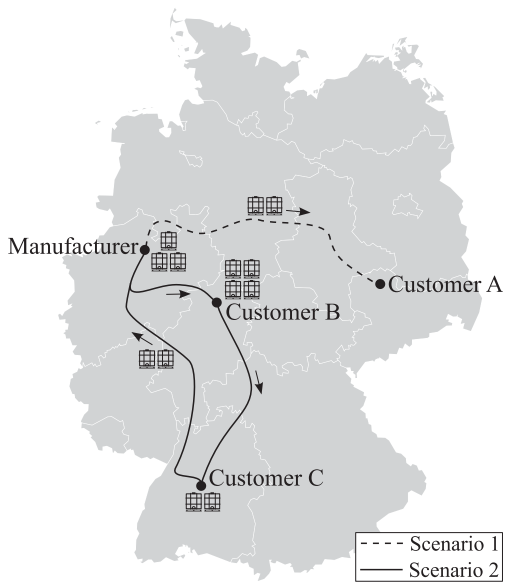


Fig. 2. The map shows two typical routing scenarios.

3.2. IBC sensor

The sensors attached to IBCs to track their location and state (e.g. temperature) can enter different modes. *Active* sensors transmit data at a constant rate, for example, once per hour. When sensor enter the *sleep* mode, no data is transmitted and the sensor can only be activated via specific control commands or when the sensor measures a change in acceleration. This feature is necessary to detect the life cycle transitions. The sensors are *off* when the battery is empty.

Although IBCs go through multiple cycles before the battery of the sensor is depleted, the sensors transmit much redundant information that does not provide any additional value to the customer, especially in cases where IBCs are stored or moved in bulk. Hence, there is an opportunity to reduce the energy consumption of sensors through a control algorithm that can extend their life span and decrease the maintenance costs of the system. In particular, the problem we address in this study is to *optimise the overall sensor energy consumption while maintaining acceptable quality of data for each phase of the process*. The quality of data is deemed to be acceptable if the information necessary to make decisions is available.

3.3. Tracking-influenced decisions

A high quality of available IBC data is paramount to improve customer service and rapidly react to disruptions that occur during transport. There are two main decisions that are affected by the monitoring and tracking information:

(1) **Carrier:** in many cases trucks require a temperature control unit to transport sensitive products because the temperature has an effect on the functionality of the product. Furthermore, spillages may be caused by unexpected high impacts, for example, due to a truck accident. Using the tracking and monitoring information, the manufacturer *needs to decide if a truck requires rerouting* to proactively prevent irreversible damage to the product and guarantee that the containers arrive in time.

(2) **Customer:** customers typically do not keep track of the fill level of individual IBCs, which can cause delays in processes at the customer. Based on the fill level data of IBC sensors, the manufacturer *needs to schedule replenishment routes* to reduce the downtime of processes at the customer. The location data can be utilised in cases where sites have a dedicated shipping area that store empty containers.

In the following section we present the agent model that is used to supervise and reduce the energy consumption of sensors while maintaining an acceptable quality of data throughout the different life cycle phases of an IBC.

4. Agent-based energy-efficient monitoring

In this study we propose an agent-based approach to manage and reduce the energy consumption of IBC sensors. The rationale behind using agents is twofold: first, the position of IBCs is dynamic. Depending on the life cycle phase, IBCs are moved from the manufacturer to the customer and vice versa, yielding new sets of clustered IBCs for each movement. Second, the IBCs have some level of autonomy. In particular, the sensor data on each IBC can be transmitted at certain rates, sudden changes in acceleration trigger the activation of sensors, and notifications are sent if the battery level falls below a threshold. The aim is to induce collaboration among IBC sensors, such that they are able to dynamically adapt to specific situations. These situations require the sensing to be *data-driven*, since the activity of IBC sensors is controlled based on the data they perceive. An agent-based model enables a representation of these dynamics and capabilities. In the short term agents are able to recreate IBC characteristics in a model and simplify the implementation of sensor control functions at an individual IBC level and in the long term they can track the changes individual IBCs encounter throughout their life cycle.

4.1. Agent model

Agent models represent the individual agents, their interactions, and the environment (Herrera et al., 2020). The proposed agent model, as shown in Fig. 3, abstracts each IBC sensor by an agent. The agent gathers data from the sensor and controls it through actions. Due to the agents' autonomy and ability to interact with each other, various cooperative and coordinated control algorithms can be implemented. In order to increase the energy efficiency of the sensors, the agents operate on the cloud and relevant process information is sent to a dashboard application for visualisation. This study concentrates on modelling the dynamics of the positions of IBCs throughout their life cycle.

4.2. Clustering and life cycle detection

There are three main coordination functions that are executed at each agent step, which are illustrated in Figs. 4(a) to 4(c). Initially, all sensors are set to be active and will transmit data at a constant rate. The first function clusters the agents based on the global position of IBCs provided by the sensors. There are a number of clustering algorithms that can be adopted for this scenario: for example, *k-means* (Arthur and Vassilvitskii, 2007) aims to identify clusters by minimising the average squared distance between observations within the same cluster. The number of clusters can be estimated by grouping agents based on the location differences. As a nonparametric algorithm, *Mean Shift* (Comaniciu and Meer, 2002) locates clusters by maximising a density function. *DBSCAN* (Ester et al., 1996) distinguishes between dense and thin population areas by specifying points that can be reached within a predefined neighbourhood distance. Based on the determined clusters, the second function of the agent-based sensor management selects a cluster leader, a sensor which remains active and continues to transmit data, while the other sensors are put into sleep mode. The agents establish this cluster leader based on the battery levels of clustered sensors. That is, the sensor with the highest battery level is elected to be the cluster leader for the next coordination step, which guarantees that the energy is consumed evenly. If an agent cannot be assigned to a cluster, its sensor remains active. Finally, the third function determines the life cycle phase for each IBC by computing the difference between its current and previous position as well as the distance to the fixed locations of the sites of the customers and

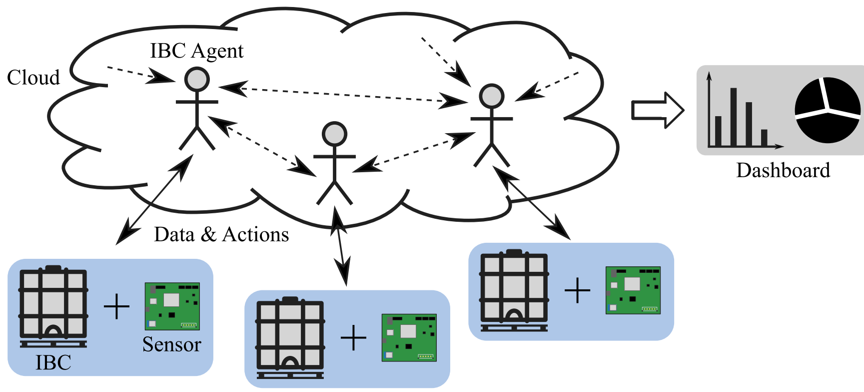


Fig. 3. The proposed agent model.

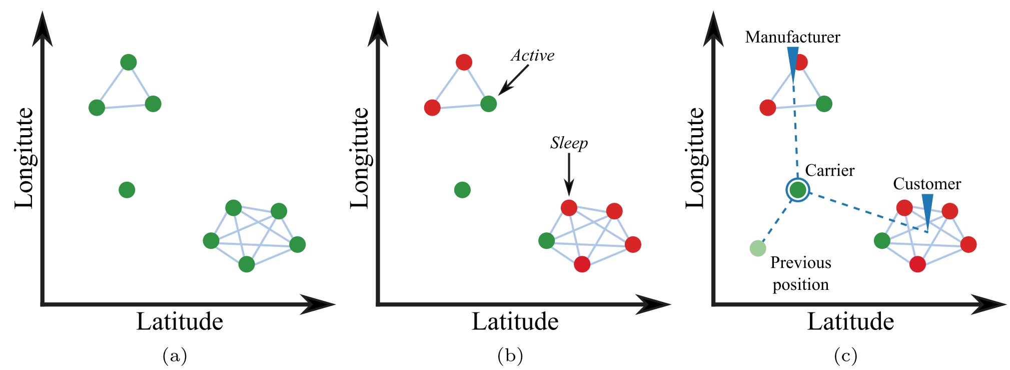


Fig. 4. Agent-based sensor management: (a) The sensor clustering algorithms detects groups of IBC agents. (b) The sensor cluster leader selection determines one active sensor which continues to transmit data, while others are put into sleep mode. (c) The life cycle detection identifies the life cycle phase for each IBC agent based on their current and previous position.

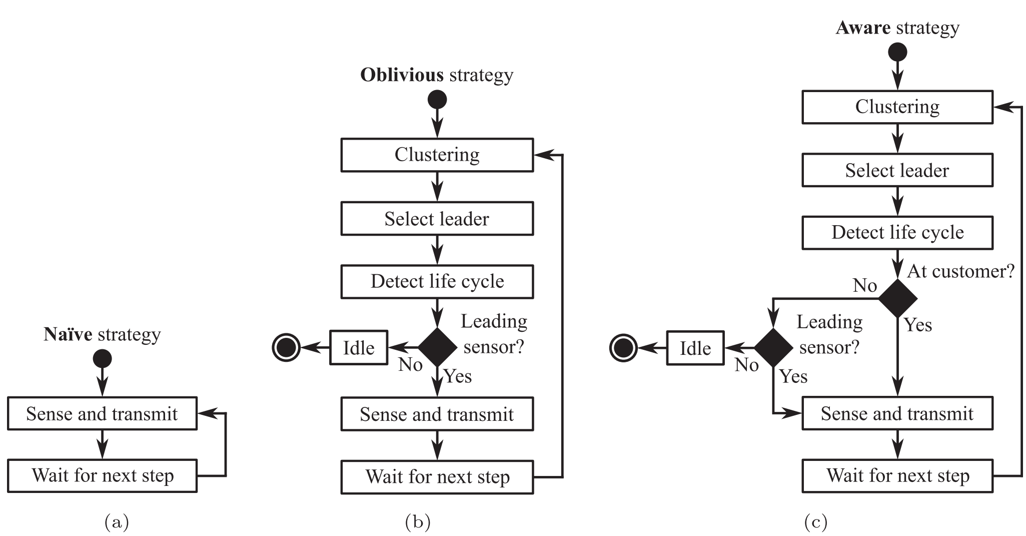


Fig. 5. The main coordination approaches of an agent-based sensor management system following the (a) Naïve, (b) Oblivious, or (c) Aware energy efficiency strategy.

manufacturer. The three functions are described by Algorithm 1. The time complexity of Algorithm 1 mainly depends on the two loops and the clustering algorithm chosen. *K-means*, *Mean Shift* and *DBSCAN* have well-known complexities based on the parameters used by each algorithm. Assuming S are the factors driving the complexity of the clustering algorithm chosen and $O(S)$ is its complexity, then the complexity of Algorithm 1 is between $O(N^2)$, when $O(S) \leq O(N)$, and $O(N \times S)$ for $O(S) > O(N)$.

Algorithm 1 Clustering and life cycle detection at each model step x for N agents for the Oblivious and Aware strategy. For the Naïve approach, these functions are not executed because the agents do not schedule the sensor activity.

```
P ← getAgentsPositions(x)    ▷ Get the positions P of agents at step x
B ← getAgentsBatteryLevels(x)
Choose an energy-efficiency strategy s
for a = 1 to N do
    C ← doClustering(P)    ▷ Determine the clusters C for all agents
    c ← getAgentCluster(C, a)    ▷ Select cluster c that includes agent a
    if |c| > 1 then    ▷ If the cluster includes more than one agent
        B_max ← 0
        for a_c in c do
            if B(x, a_c) > B_max then    ▷ Check the battery level B
                a_leader ← a_c    ▷ Select the new cluster leader a_leader
            end if
        end for
    end if
    if s is Aware then
        if |P(x, a) − P(x−1, a)| > ε then    ▷ If the agent position has changed
            L_C(x, a) ← carrier    ▷ Update life cycle phase L_C
        else if |P(x, a) − P_M| < ε then    ▷ If the agent is near the manufacturer
            L_C(x, a) ← manufacturer
        else if |P(x, a) − P_C| < ε then    ▷ If the agent is close to the customer
            L_C(x, a) ← customer
        end if
    end if
end for
```

4.3. Energy efficiency strategies

Multi-agent systems can employ various strategies to achieve a system goal, which can be implemented through a set of rules each agent has to follow. For the industrial application provided in this study, we propose three agent strategies to regulate the energy consumption of sensors. Figs. 5(a) to 5(c) depict the main control flows of a given agent that follows one of the suggested coordination strategies:

- **Naïve Coordination.** For the Naïve strategy, agents merely monitor the relevant IBC sensors without scheduling their activity. All sensors remain active and transmit data to the cloud at a constant rate. This strategy serves as a baseline for the following two approaches by estimating the base consumption of the monitoring application.
- **Oblivious Coordination.** This strategy applies the clustering algorithm and selects a leading sensor for each cluster. Instead of gathering the data of all IBC sensors in the cluster, the leading IBC sensor merely sends information about its own state while the others are put into sleep mode (i.e. it assumes all other IBC sensors are identical). Using this approach agents disregard the life cycle transitions of IBCs.
- **Aware Coordination.** Besides being clustered and electing a leading sensor for a given cluster, agents detect the life cycle phase of IBCs and schedule the sensor activity accordingly. Based on the information required to make decisions described in Section 3.3, the sensors at the customer remain active to monitor the individual fill level alterations, while containers in transit and at the manufacturer follow the Oblivious strategy.

4.4. Evaluation metrics

To compare and evaluate the three energy efficiency strategies, we define two metrics: the energy savings S_E is used to assess the effect of the different agent strategies on the energy consumption. The information loss L_I captures the impact of the sensor management on the available information. These metrics quantify the trade-off between the energy consumption reduction and available (necessary) information of the monitoring system to make decisions.

The energy savings metric captures the relative difference of the battery levels between a given strategy and the Naïve approach averaged over all agents for a fixed interval:

$$S_E = \frac{1}{N} \sum_{a=0}^{N} \frac{\int_K B(x,a)\,dx - \int_K B_{naïve}(x,a)\,dx}{\int_K B(x,a)\,dx}, \tag{1}$$

where K is the number of simulation steps of the agent model, $B(x,a)$ is the battery level at step x obtained from the sensors modelled by agent a, and N is the total number of agents of the model.

As scheduling the node activity potentially yields several inactive sensors which are not transmitting data, there is less information available to track the state of all containers. The information loss measures this lack of information by computing the percentage of active sensors with a sufficiently high battery level to transmit data:

$$\begin{aligned} L_I &= \frac{1}{K}\sum_{x=0}^{K} L_I(x) \\ &= \frac{1}{K}\sum_{x=0}^{K} 1 - \frac{1}{N}\,\mathrm{card}(\{a : M(x,a) \text{ is } active\} \cap \{a : B(x,a) > 0\}), \end{aligned} \tag{2}$$

where K is the number of steps of the agent model, $M(x,a)$ is the mode of an agent a at a given step x, $B(x,a)$ is the battery level obtained from a specific sensor at a given step, and N is the total number of agents.

As the information loss strictly increases with the number of inactive sensors, we argue to *weight the information loss by its necessity*. In situations where information is *necessary* to make decisions, it is crucial that the lack of it (due to the energy efficiency strategies) does not affect the capability of the manufacturer or customer to make decisions:

$$L_{I,w} = \frac{1}{K}\sum_{x=0}^{K} w(x)\, L_I(x)\,. \tag{3}$$

We focus on the weighted information loss $L_{I,w}$ in this study because this metric is of higher relevance for the manufacturer to assess the quality of data when using the different coordination strategies. The (unweighted) information loss L_I metric merely serves as a reference for $L_{I,w}$.

Based on the decisions described in Section 3.3, the agent strategies are subject to two constraints: (a) at least one sensor needs to be active at the manufacturer and during transport to track the movement, and (b) at the customer all sensors need to be active to monitor the fill level changes of individual IBCs. These constraints form the basis for the weights w, which capture the percentage of sensors that need to be active and transmit information for each cluster depending on the current life cycle phase of an IBC. At each step, the weight compares the number of active sensors needed for a current life cycle phase with the number of active sensors given at each identified cluster:

$$w(x) = \frac{1}{N_c(x)} \sum_{i=0}^{N_c(x)} 1 - \frac{g(x) - n(x)}{N}, \tag{4}$$

where N is the total number of agents in the model, N_c if the number of IBC clusters at step x, and

$$g(x) = \mathrm{card}(\{a_c : M(x,a_c) \text{ is } active\}) \tag{5}$$

represents the number of active sensors a_c *given* in a cluster c at step x, and

$$n(x) = \max(\mathrm{card}(\{a_c : L_C(x,a_c) \text{ is } customer\}), 1) \tag{6}$$

is the number of active sensors *needed* in a cluster c at step x, where $L_C(x, a_c)$ describes the current life cycle phase of an IBC agent a_c in a cluster. If more sensors are active than needed, the weight decreases the information loss, otherwise, the information loss increases.

5. Simulation study

To show the effect of different agent-based sensor management approaches on the energy consumption throughout the IBC life cycle, this paper conducts a simulation of the two routing scenarios described in Fig. 2. While for the first scenario the IBCs remain in a single cluster, in the second scenario the containers are split up between the manufacturer and the two customers. At the customers, the same number of empty containers are replaced with filled IBCs such that the absolute number of containers at both customers does not change. Consequently, the two scenarios can be repeated several times to analyse the effect of agents on the energy consumption in the long term. The simulation is stopped once the first sensor reaches a battery level of 0 because the monitoring systems becomes unreliable when agents are no longer able to coordinate and fetch data from the sensors.

In the following two sections, we describe the simulation assumptions for the energy consumption of IBC sensors, and outline the implementation of the simulation conducted in this study.

5.1. Energy consumption of sensors

The energy consumption of IBC sensors is estimated based on a deterministic model developed by Dusza et al. (2012), which differentiates between different power states of a device. The model provides an empirically derived representation of the power consumption of data transmitted via user equipment. User equipment, such as smartphones, is comparable to the IBC sensors used in this study, because they include similar hardware components and firmware. The emitted transmission power is approximated by two linear functions:

$$\bar{P}(P_{Tx}) = \begin{cases} \alpha_L\, P_{Tx} + \beta_L & \text{for } P_{Tx} \leq \gamma \\ \alpha_H\, P_{Tx} + \beta_H & \text{for } P_{Tx} > \gamma \end{cases} \tag{7}$$

with device specific parameters α, β and γ and the uplink transmission power P_{Tx}. The downlink reception can be estimated by the β_L parameter. As the typical routing scenarios of IBCs are subject to large distances between customer and manufacturer, we assume that the data transfer requires the maximum power transmission allowed of 23 dB.[1]

To determine how long the device remains in a particular power state, we need to specify the time it takes to transmit the sensor data. The time to transmit the data t_{Tx} is based on the package size D and the achievable throughout T:

$$t_{Tx} = \frac{D}{T} \tag{8}$$

The achievable throughput T is dependent on the signal-to-noise ratio (SNR) at the base station. The SNR reduces with an increasing distance d between node and base station because the transmission power is limited and cannot compensate for the growing path loss. For large distances $d > 3$ km, we assume an SNR of 13 dB, which yields a throughput of $T = 5$ Mbit/s (Dusza et al., 2014). For specifying the package size we only consider the required payload and disregard other parts of the message, such as preamble and header, as these vary across protocols. The IBC sensors capture GPS coordinates, fill level, temperature, acceleration in X, Y and Z, battery level, and signal strength. Each parameter is augmented with a timestamp, an ID, a name, a serial number of the sensor and a field specifying the unit. Using a 64 bit floating-point arithmetic, the package size is $D = (7 + 6 + 6 + 8 + 6 + 6) \times 64\,\text{bit} = 2496\,\text{bit}$.

Based on the power consumption during the different power states and the time to transmit the data, the energy consumption E is determined depending on the rate of data transmissions f. For active and sleeping sensors the energy consumption of one cycle is computed as follows:

$$E_{active}(f) = P_{max}\, t_{Tx} + P_{low}\,(\frac{1}{f} - t_{Tx}), \tag{9}$$

$$E_{sleep}(f) = P_{idle}\, \frac{1}{f}, \tag{10}$$

where $P_{max} = \bar{P}(23\,\text{dB}) = 2.35$ W is the required power for the data transmission, $P_{low} = \beta_L$ is the receiving power state that an active sensor enters once the data has been transmitted and P_{idle} is the amount of power consumed when there are no data transmissions. For example, for a data transmission rate of once per hour, the energy consumption for one cycle is $E_{active} = 5760.000374$ J and $E_{sleep} = 144$ J.

5.2. Implementation

The agents initialise the sensors with a random value for the battery level. The data transmission rate is set to once per hour, and thus, *one simulation step corresponds to one hour passed*. Based on the adopted power consumption model, the battery level reduces by 2.339% if the sensors remain active and transmit data, and decreases by 0.059% if the sensor is "sleeping".[2] The routing scenarios are implemented using the Open Source Routing Machine (OSRM),[3] while the temperature is determined using the resulting OSRM GPS coordinates of individual IBCs and Meteostat.[4]

6. Analysis of results

To address the information redundancies and energy inefficiencies in a location tracking and state monitoring application, an agent-based model has been proposed and simulated for two typical routing scenarios. Three different sensor usage strategies have been developed and evaluated. The simulation results show that the longest network life span is achieved when the majority of sensors are put into sleep mode. However, in situations where high quality sensor data is required to make decisions, the sensors need to be made aware of the life cycle phase of IBCs. In this section we analyse the results of the simulation in terms of energy savings and information loss. To validate these results we then discuss three cases of disruptions that typically occur during the transport of IBCs and assess the effect of agent-based sensor management on the ability to handle those disruptions.

6.1. Energy savings and battery life span

To identify a suitable agent strategy for the given industrial application, we evaluate the three proposed strategies quantitatively by analysing the resulting battery life span and measuring the energy savings, which describe the relative battery level difference between a given strategy and the Naïve approach. For the two IBC routing scenarios chosen here, the energy savings S_E for each of the three proposed strategies averaged over the simulation runs are shown in Table 2.

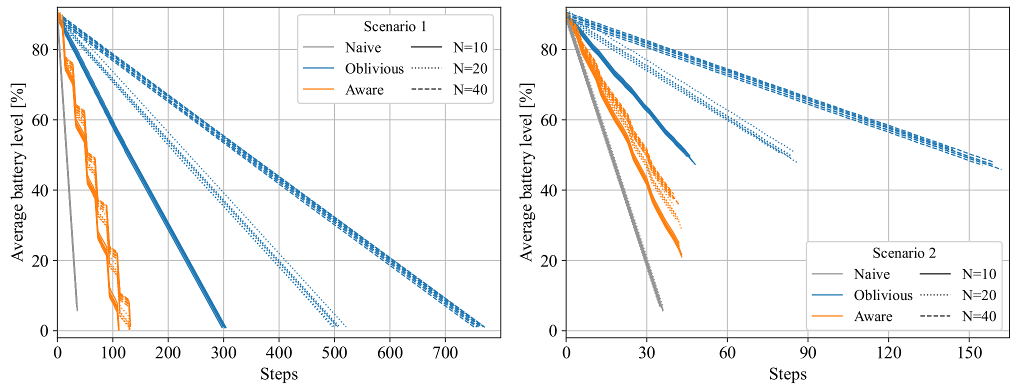
Regarding the energy savings, the Naïve strategy does not actively schedule the sensor activity and thus no energy is saved. If the IBC sensors are scheduled, however, the simulation shows that agents are capable of reducing the energy consumption. For the first routing

[1] HTC Velocity 4G with $\alpha_H = 68$ mW/dBm, $\beta_H = 0.79$ W, $\beta_L = 1.6$ W and $P_{idle} = 40$ mW with a carrier frequency LTE Band 7 @800 MHz (Dusza et al., 2012).

[2] Battery cell: Li-SoCl2 TekCell ER34615J-S with a nominal voltage $U = 3.6$ V and a nominal capacity $C = 19\,000$ mAh.

[3] http://project-osrm.org/.

[4] https://meteostat.net/en/.



(a) (b)

Fig. 6. Overall energy consumption for the (a) first and (b) second routing scenario based on the three energy efficiency strategies averaged over 10, 20 and 40 agents for 7 simulation runs. One simulation step corresponds to one hour past. Each line represents the *average* of 10, 20, and 40 sensor battery levels.

Table 2
Energy savings S_E and (weighted) information loss L_I and $L_{I,w}$ for the three energy efficiency strategies based on a different number of simulated agents for the two routing scenarios averaged over 7 simulation runs.

	Strategy	Scenario 1			Scenario 2		
		N			N		
		10	20	40	10	20	40
S_E	Naïve	0	0	0	0	0	0
	Oblivious	0.873	0.926	0.951	0.463	0.708	0.841
	Aware	0.664	0.702	0.720	0.279	0.318	0.327
L_I	Naïve	0.003	0.003	0.003	0.003	0.003	0.003
	Oblivious	0.718	0.759	0.780	0.490	0.660	0.750
	Aware	0.543	0.584	0.590	0.245	0.316	0.351
$L_{I,w}$	Naïve	–	–	–	–	–	–
	Oblivious	0.879	0.938	0.969	0.519	0.715	0.821
	Aware	0.543	0.584	0.590	0.243	0.313	0.348

scenario, as the strategy with the largest percentage of sleeping sensors, the Oblivious strategy saves the most energy from 87%, for 10 agents, to 95%, for 40 agents. For the second scenario, less energy is saved because there are more clusters and the number of active sensors at each step is therefore higher. When agents are aware of the life cycle phase and the sensors remain active when residing at the customer, the energy is consumed at an accelerated rate, because the total number of active sensors of the monitoring system is larger compared to the Oblivious strategy. Similar to the Oblivious approach, less energy is saved for the second routing scenario. Additionally, the total number of monitored IBCs has an effect on the energy savings. As more IBCs can be clustered, an increasing number of sensors are put into sleep mode, leaving a single sensor active to represent the whole cluster. Therefore, the more IBCs are clustered, the more energy is saved.

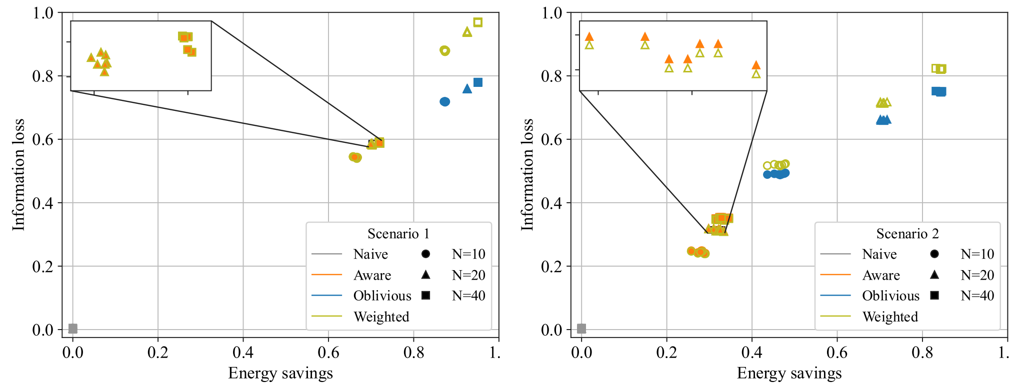
The average energy consumption and battery life span for the two scenarios over the simulation time for the three strategies are depicted in Figs. 6(a) and 6(b). In contrast to the Naïve and Oblivious strategy, whose average battery level decreases linearly, the Aware approach results in discontinuities in the energy consumption, because its node activity changes dynamically based on the current life cycle. While for the Naïve and Oblivious approach the number of active and sleeping sensors rarely changes, agents that are aware of the life cycle activate sensors when the containers reside at the customer, leading to a higher energy consumption. Similar to the energy savings, the Oblivious strategy results in the longest battery life span of 760 h and 158 h for 40 agents for the first and second scenario, respectively, which is an increase of ×21.7 and ×4.5 compared to the baseline. In contrast, as more agents are active for the Aware strategy, the life span is only extended by ×3.7 and ×1.2. Equivalent to the energy savings, the life span also increases with the number IBCs in a single cluster for both the Oblivious and Aware strategy. However, for the latter only small increases in the life span and energy savings can be observed, because, for the routing scenarios chosen, the IBCs are at the customer for large periods of time, which negatively affects the energy consumption. It is noteworthy to mention that the average battery level is significantly different for both scenarios when the stopping criterion of the simulation is met, which is due to the fact that the IBCs have a different movement pattern for both scenarios. For the first route, IBC remain in a single cluster for the whole duration of the simulation, while for the second scenario the containers split up and recombine along the route. This yields smaller clusters which in turn leads to an increased energy consumption.

Generally, the main factors that affect the energy savings and the battery life span for the scenarios in this study include the number of clustered IBCs and the chosen agent strategy. The energy consumption decreases with the number of clustered containers because more sensors can be allocated to the same cluster, put into sleep mode and are therefore not required to transmit data. Further, the agent strategy plays an important role in reducing the overall energy consumption as it dictates how many sensors remain active. Additionally, the design and implementation of the monitoring system has an effect on the energy efficiency as well, in particular, resource demanding algorithms running on the edge ought to be avoided.

6.2. Information loss

As a subset of sensors are deliberately put into sleep mode to increase the overall energy efficiency, the available sensor information at a given step is reduced. It is crucial to analyse this loss of information with respect to the energy saved in order to evaluate the effect of the proposed strategies on the decision making in specific situations. However, as the lack of information strictly increases with the number of inactive sensors, we weight the information loss by its necessity. For two routing scenarios in this study, the average (weighted) information loss L_I and $L_{I,w}$ for each energy efficiency strategy is shown in Table 2, whereas the relationship between the energy savings and the information loss is depicted in Figs. 7(a) and 7(b).

The loss of available IBC information linearly increases with the number of sleeping sensors and therefore with the energy saved. Consequently, the highest information loss is achieved by the Oblivious strategy. For the Aware strategy, the loss of information is lower due to the sensors being active when IBCs are at the customer. The Naïve strategy has an information loss marginally above zero, since the simulation stops once the first battery is empty which yields a single inactive sensor at the last step.



(a) (b)

Fig. 7. The relationship between the energy savings S_E and the (weighted) information loss L_I and $L_{I,w}$ for the (a) first and (b) second routing scenario based on the three energy efficiency strategies averaged over 10, 20 and 40 agents for 7 simulation runs.

As a metric, the information loss is unable to distinguish between important and negligible data. In particular, it does not cover the specific situations IBC face during different life cycle phases. For instance, when transported on a truck, IBCs are likely to undergo the same environmental conditions, and thus the majority of sensors would send redundant information. Therefore, we *weight the information loss by its necessity* in order to analyse the effect of the energy efficiency strategies on the capability to make decisions in specific situations. The weighted information loss can only be evaluated for the Oblivious and Aware strategy, since for the Naïve approach, no clustering is performed and thus the metric cannot be applied.

As the Oblivious strategy enforces to put sensors into sleep mode regardless of the individual IBC life cycle phase, it does not satisfy the second constraint, which requires all sensors to be active when containers are at the customer. Therefore, the weights increase the information loss on average by 19.0% for the first and 7.3% for the second scenario. On the other hand, the weighted information loss for the Aware strategy differs for both IBC routing scenarios. For the first scenario, all IBC remain in a single cluster throughout the duration of the simulation, which satisfies both constraints imposed by the decisions described in Section 3.3. This strategy ensures that for the manufacturer and carrier life cycle at least one sensor is active, while at the customer all sensors transmit data. Therefore the weights do not change the information loss. In contrast, the second scenario divides the IBCs into multiple clusters during different phases of their life cycle. During the simulation, the clusters are recombined at the customer and manufacturer performing loading and unloading operations. In those situations more sensors are active than needed, which decreases the information loss on average by 0.9% for different numbers of agents.

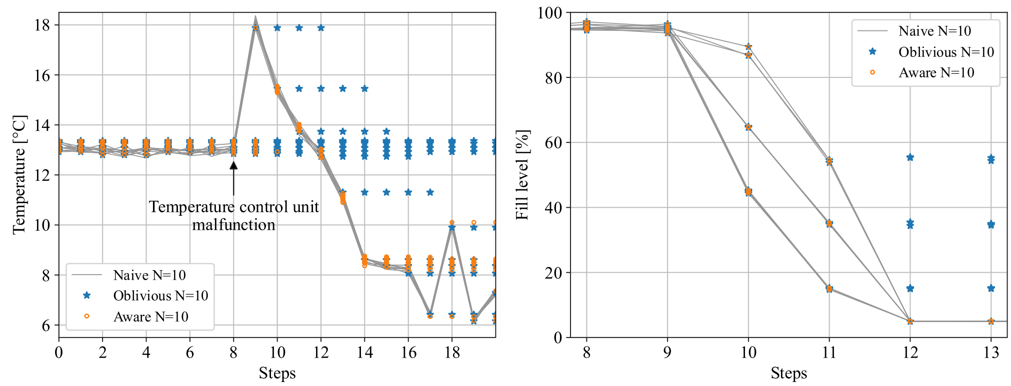
Similar to the energy savings, the main factors that affect the information loss is the chosen agent strategy. Although the Oblivious strategy yields the highest energy savings, it puts sensors into sleep mode in situations in which a high quality of data is crucial to make decisions. In contrast, the Aware strategy compensates for this by activating more sensors in those situations. This effect is emphasised by weighting the loss of information.

6.3. Exceptional cases

To validate the results of weighting the information loss and to demonstrate the effect of the agent strategies on the decision making, we conduct additional experiments with the proposed agent-based model. In particular we simulate and discuss three cases of disruptions that typically occur during the transport of IBCs and assess the effect of the different energy efficiency strategies on the capability of handling those disruptions: (1) the temperature control unit of a truck carrying sensitive goods fails, (2) the customer has an unexpected early demand for replenishment, and (3) a traffic jam delays the transport of IBCs. The second case is further separated into customers who do not move the containers once they are empty, and those which have a dedicated shipping area. In the following we discuss the results of simulating the three disruption cases for the first routing scenario.

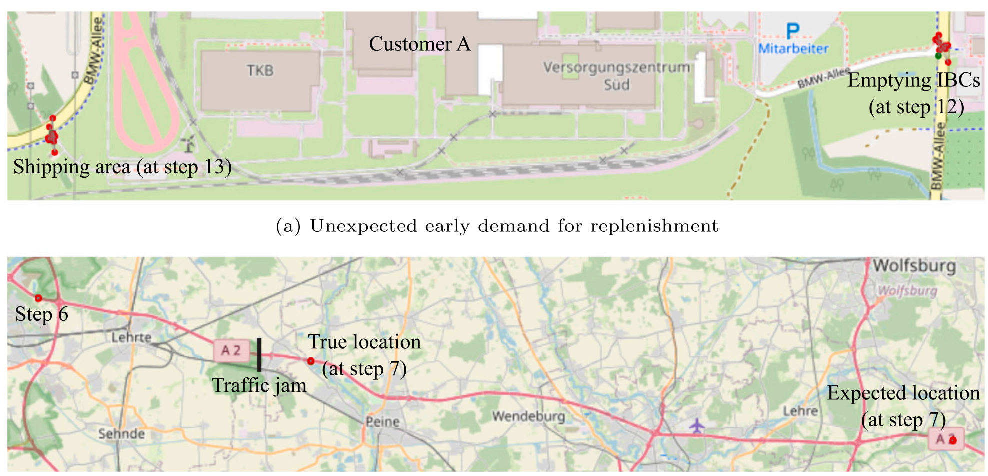
Case 1 - Temperature control unit malfunction. The temperature control unit malfunction on a truck carrying sensitive goods is illustrated in Fig. 8(a), which compares the temperature measurements of 10 sensors managed by agents following different energy efficiency strategies. The malfunction occurs at the eighth step and it is assumed that by the next step the temperature inside the truck has reached the ambient temperature. While all three energy efficiency strategies are capable of detecting the change in temperature, there are significant differences among the individual agents in terms of the way they coordinate. In contrast to the Naïve approach, for which all agents are able to observe the change in temperature, the Oblivious and Aware strategies only have a single sensor active at any given step during the transport, which yield high inaccuracies when the disruption occurs and might delay its detection. However, when the containers are at the customer between step 11 and 15, the aware agents activate all sensors until the empty containers are loaded onto the truck to return to the manufacturer, which results in fewer errors compared to the Oblivious approach.

Case 2 - Unexpected early demand for replenishment. When a truck arrives at a customer, the containers are typically being emptied at different rates. It is helpful to detect when containers are empty such that they can be replenished before they lead to significant downtimes of processes at the customer. The second disruption covers an unexpected early demand for replenishment by the customer. We further differentiate between cases where containers remain stationary and solely the fill level measurements are available to detect the disruption, which is depicted in Fig. 8(b), and situations in which empty IBCs are moved to a dedicated shipping area, which is shown in Fig. 9(a) for the Oblivious strategy. The fill level measurements can be compared to the temperature observations performed by individual agents at the customer: the Naïve and Aware strategy keep all sensors active during the emptying of IBCs and thus all agents are capable of monitoring the individual changes of fill level. When agents arrive at the customer at step 9 using the Oblivious strategy, all sensors are activated for one step. However, when the agents put most sensors back into sleep mode from step 11, the agents are not capable to track the fill level alterations of individual containers, thus resulting in more errors. On the other hand, all three agent strategies are able to capture when the containers are empty and relocated to a dedicated shipping area because for each strategy movement induces the activation of sensors regardless of their previous mode.



(a) (b)

Fig. 8. (a) Temperature measurements of individual agents for the different energy efficiency strategies as a result of simulating a temperature control unit malfunction for the first routing scenario for 10 agents. (b) Fill level measurements of individual agents for the different energy efficiency strategies when simulating an unexpected early demand for replenishment by the customer for the first routing scenario for 10 agents.



(a) Unexpected early demand for replenishment

(b) Traffic jam

Fig. 9. Simulation of two typical disruptions when routing IBCs.

Case 3 - Traffic jam. The sensors can also serve as a tracker for the truck itself. The transportation of IBCs is usually subcontracted to an external freight forwarder, which for the most part only logs the start and arrival time. In case of a traffic jam along the route, it is crucial to know the exact position of the truck to determine a good estimate of the arrival time at the customer before completing the route. Fig. 9(b) displays this disruption for the Oblivious strategy, where the true location vastly deviates from the expected position at a given step. Clearly, all three energy efficiency strategies are able to capture the disruption in traffic, because merely a single active sensor that serves as the cluster leader is sufficient to track the location of the truck, whereas the Naïve approach results in much unnecessary information being sent.

The three cases of disruptions validate the results of the information loss analysis for the different agent strategies: while the Naïve strategy is able to capture and track the disruptions for each individual container, the Oblivious strategy is only able to spot the changes at the cluster level. As a hybrid strategy, agents that are aware of the individual life cycle phase perform similarly to those based on the Naïve approach while simultaneously preserving more energy.

7. Discussion

In this section, we discuss the limitations of this study and describe the lessons learnt from applying an agent-based approach to the location tracking and state monitoring system in the context of transport of liquid goods. We additionally outline implications for future endeavours of using agent-based management in similar logistics processes.

7.1. Limitations

This study is subject to the following limitations: first, the proposed agent model is tailored towards the application of location tracking and state monitoring in the context of transport of liquid goods. The characteristics of this specific monitoring application include (a) a large-scale highly distributed network, whereby the state and location of IBCs (i.e. nodes) change readily, and (b) the data requirements for different situations of the monitored goods vary. Such situations include the three different life cycle phases of IBCs and the disruptions that may occur during transit. As described in Section 2.5, applying existing energy efficiency strategies for WSNs is therefore not feasible. Second, the available data of this application is limited. While in this study two typical routing scenarios have been considered, more data is required to capture the whole range of IBC routing patterns. Therefore, reproducing other more general energy-efficient tracking strategies for WSNs is difficult. Third, while we have shown that an agent-based approach is capable of identifying inefficiencies in the considered monitoring application, there is a need for analysing if the proposed strategies are most efficient in reducing the energy consumption of IBC sensors.

7.2. Lessons learnt

We finally discuss the lessons learnt from applying an agent-based approach to the coordination of the monitoring system of containers in transport and outline implications for future endeavours of using agent-based management in logistics processes. While merely a subset of aspects of the real system can be captured by the simulation, there are a number of learnings that can be drawn from applying the agent model to the simulated environment, which can be projected to the physical instantiation of the monitoring system:

- Adjusting the system information for relevance reduces the perceived loss of system information. To minimise the energy consumption several sensors are put into sleep mode in specific situations, which decreases the amount of available information about the system state. However, not all information is relevant for the end user and thus some data can be neglected without compromising the capability of making decisions that depend on this information.
- More computational power is required to run advanced machine learning algorithms as the system is only optimised for energy efficiency. Though, developers need to consider the trade-off between the energy savings as a result from the agent model and the increasing expenses in the computer infrastructure.
- There are no significant differences when testing the three clustering detection algorithms, because the distance to neighbouring clusters is large compared the distances of nodes within a cluster. The algorithms *k-means*, *Mean Shift* and *DBSCAN* identify the same clusters in the scenarios chosen for this study. The different algorithmic runtimes are not critical for the system performance, since the rate of data transmissions is typically not higher than once per hour.
- We argue that the proposed agent model is *unlikely to suffer from visibility and scalability issues for this particular logistics application*. In terms of visibility, each agent has access to the information of all other agents in the system (including the sensor battery level, signal strength etc.), because the model runs in the cloud. As a consequence of sleeping sensors, however, some information may be outdated at query time. Regarding scalability, a cluster of IBCs is unlikely to grow indefinitely, but its size has an upper limit due to limitations of the underlying physical system. Specifically, IBCs will eventually fill up a warehouse and remnants have to be stored in another location, which would yield a new cluster.

Additional recommendations to increase the energy efficiency can be deducted from the simulation of the agent model, particularly in terms of warehousing IBCs as well as planning and scheduling their routes:

- IBCs should be transported and stored in bulk whenever possible such that the agent strategies can form clusters with a large number of sleeping sensors to maximise the energy savings.
- Multiple battery cells should be stacked to increase the life span of sensors, since the weight imposed by the additional cells is negligible compared to the weight of the containers.

8. Conclusions and future work

In this study, we have applied the agent methodology to an industrial monitoring application in logistics and demonstrated that agents help to analyse energy inefficiencies of the application and are capable of increasing the battery life span of networked sensors. To tackle the energy inefficiencies of the system, three different agent strategies have been proposed. When weighting the information loss by its necessity to make decisions, the results show that agents that are aware of the different life cycle phases of a container achieve the best performance in terms of energy savings and information loss. In contrast, the longest life span of batteries is achieved when the majority of sensors are put into sleep mode yielding an increase of $\times 21.7$ and $\times 3.7$ for two typical routing scenarios. Additionally, we have validated the effect of the agent strategies on the decision making by simulating three cases of disruptions that typically occur during transportation.

There are numerous research directions that can be taken to enhance the monitoring application: first, advanced data analytics can be incorporated when the agent model is implemented. For instance, a data-driven approach can be developed which leverages the information gathered by the IBC sensors. The trained model could then be used to predict the life cycle of different types of IBCs or construct various risk profiles based on the disruptions captured by agents. Second, there is a need to implement more sophisticated agent strategies to further reduce the energy consumption and compare those with global sensor scheduling mechanisms presented in the literature. Third, the localisation of containers via GPS is subject to noise, especially when IBCs are stored in a warehouse. The agent model could be used to increase the positional accuracy. Fourth, as indicated earlier, IBCs are being emptied by the customer at different rates. There is need to study the fill level dynamics of individual containers to improve the transportation schedules. Fifth, in terms of the hardware power consumption, agents could be used to further improve the energy efficiency by providing controls for the power state transitions. In particular, once an active sensor has transmitted the data, it could return into sleep mode instead of remaining in a more power-hungry state. Finally, the monitoring application discussed here can be analysed in terms of the value of information. Specifically, the effect of the monitoring information on the different types of actions and decisions can be studied.

CRediT authorship contribution statement

Jan Kaiser: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Marco Pérez Hernández:** Conceptualization, Methodology, Software, Investigation, Data curation, Writing – review & editing , Visualization. **Victor Kaupe:** Conceptualization, Methodology, Investigation, Data curation, Writing – review & editing. **Philip Kurrek:** Conceptualization, Methodology, Investigation, Data curation. **Duncan McFarlane:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

Arthur, D., Vassilvitskii, S., 2007. K-means++: The advantages of careful seeding. pp. 1027–1035.
Arumugam, S.S., Umashankar, V., Narendra, N.C., Badrinath, R., Mujumdar, A.P., Holler, J., Hernandez, A., 2018. IoT enabled smart logistics using smart contracts. ISBN: 9781538669655, http://dx.doi.org/10.1109/LISS.2018.8593220.
Athanasiadis, I.N., Mitkas, P.A., 2004. An agent-based intelligent environmental monitoring system. Manag. Environ. Qual. Int. J. 15, 238–249. http://dx.doi.org/10.1108/14777830410531216.
Atzori, L., Iera, A., Morabito, G., 2010. The internet of things: a survey. Comput. Netw. 54, 2787–2805. http://dx.doi.org/10.1016/j.comnet.2010.05.010.
Cao, D., Zheng, B., Ji, B., Lei, Z., Feng, C., 2020. A robust distance-based relay selection for message dissemination in vehicular network. Wirel. Netw. 26, 1755–1771. http://dx.doi.org/10.1007/s11276-018-1863-4.
Cardei, M., Wu, J., 2006. Energy-efficient coverage problems in wireless ad-hoc sensor networks. Comput. Commun. 29, 413–420. http://dx.doi.org/10.1016/j.comcom.2004.12.025.

Chow, H.K., Choy, K.L., Lee, W.B., 2007. A dynamic logistics process knowledge-based system - an RFID multi-agent approach. Knowl.-Based Syst. 20, 357–372. http://dx.doi.org/10.1016/j.knosys.2006.08.004.

Comaniciu, D., Meer, P., 2002. Mean shift: A robust approach toward feature space analysis. IEEE Trans. Pattern Anal. Mach. Intell. 24, 603–619. http://dx.doi.org/10.1109/34.1000236.

Din, S., Paul, A., Ahmad, A., Kim, J.H., 2019. Energy efficient topology management scheme based on clustering technique for software defined wireless sensor network. Peer-to-Peer Netw. Appl. 12, 348–356. http://dx.doi.org/10.1007/s12083-017-0607-z.

Dusza, B., Ide, C., Cheng, L., Wietfeld, C., 2014. An Accurate Measurement-Based Power Consumption Model For LTE Uplink Transmissions. Institute of Electrical and Electronics Engineers (IEEE), pp. 49–50. http://dx.doi.org/10.1109/infcomw.2013.6970731.

Dusza, B., Ide, C., Wietfeld, C., 2012. Measuring the impact of the mobile radio channel on the energy efficiency of LTE user equipment. ISBN: 9781467315449, http://dx.doi.org/10.1109/ICCCN.2012.6289186.

Ester, M., Kriegel, H.-P., Sander, J., Xu, X., 1996. A density-based algorithm for discovering clusters in large spatial databases with noise. pp. 226–231.

Fissaoui, M.E., Beni-Hssane, A., Saadi, M., 2017. Mobile agent protocol based energy aware data aggregation for wireless sensor networks. Procedia Comput. Sci. 113, 25–32. http://dx.doi.org/10.1016/j.procs.2017.08.279, The 8th International Conference on Emerging Ubiquitous Systems and Pervasive Networks (EUSPN 2017) / The 7th International Conference on Current and Future Trends of Information and Communication Technologies in Healthcare (ICTH-2017) / Affiliated Workshops.

Herrera, M., Pérez-Hernández, M., Parlikad, A.K., Izquierdo, J., 2020. Multi-agent systems and complex networks: Review and applications in systems engineering. Processes 8, http://dx.doi.org/10.3390/pr8030312.

Hribernik, K.A., Warden, T., Thoben, K.-D., Herzog, O., 2010. An internet of things for transport logistics - an approach to connecting the information and material flows in autonomous cooperating logistics processes. pp. 54–67.

Intanagonwiwat, C., Govindan, R., Estrin, D., Heidemann, J., Silva, F., 2003. Directed diffusion for wireless sensor networking. IEEE/ACM Trans. Netw. 11, 2–16. http://dx.doi.org/10.1109/TNET.2002.808417.

Jedermann, R., Behrens, C., Westphal, D., Lang, W., 2006. Applying autonomous sensor systems in logistics-combining sensor networks, RFIDs and software agents. Sensors Actuators A 132, 370–375. http://dx.doi.org/10.1016/j.sna.2006.02.008.

Kayikci, Y., 2018. Sustainability Impact of Digitization in Logistics, Vol. 21. Elsevier B.V., pp. 782–789. http://dx.doi.org/10.1016/j.promfg.2018.02.184.

Kelepouris, T., McFarlane, D., Giannikas, V., 2012. A supply chain tracking model using auto-ID observations. Int. J. Inf. Syst. Supply Chain Manag. 5, 1–22. http://dx.doi.org/10.4018/jisscm.2012100101.

Kumar, S.V.S., Palanichamy, Y., Selvi, M., Ganapathy, S., Kannan, A., Perumal, S.P., 2021. Energy efficient secured k means based unequal fuzzy clustering algorithm for efficient reprogramming in wireless sensor networks. Wirel. Netw. 27, 3873–3894. http://dx.doi.org/10.1007/s11276-021-02660-9.

Logambigai, R., Ganapathy, S., Kannan, A., 2018. Energy–efficient grid–based routing algorithm using intelligent fuzzy rules for wireless sensor networks. Comput. Electr. Eng. 68, 62–75. http://dx.doi.org/10.1016/j.compeleceng.2018.03.036.

Morstyn, T., Hredzak, B., Agelidis, V.G., 2018. Control strategies for microgrids with distributed energy storage systems: An overview. IEEE Trans. Smart Grid 9, 3652–3666. http://dx.doi.org/10.1109/TSG.2016.2637958.

Muhuri, P.K., Shukla, A.K., Abraham, A., 2019. Industry 4.0: A bibliometric analysis and detailed overview. Eng. Appl. Artif. Intell. 78, 218–235. http://dx.doi.org/10.1016/j.engappai.2018.11.007.

Oh, H., Bahn, H., Chae, K.J., 2005. An energy-efficient sensor routing scheme for home automation networks. IEEE Trans. Consum. Electron. 51, 836–839. http://dx.doi.org/10.1109/TCE.2005.1510492.

Parlikad, A.K., McFarlane, D., 2007. RFID-based product information in end-of-life decision making. Control Eng. Pract. 15, 1348–1363. http://dx.doi.org/10.1016/j.conengprac.2006.08.008.

Qi, H., Iyengar, S.S., Chakrabarty, K., 2001. Multiresolution data integration using mobile agents in distributed sensor networks. IEEE Trans. Syst. Man Cybern. C 31, 383–391. http://dx.doi.org/10.1109/5326.971666.

Rocha, A.D., Peres, R., Barata, J., 2015. An Agent Based Monitoring Architecture for Plug and Produce Based Manufacturing Systems. Institute of Electrical and Electronics Engineers Inc., pp. 1318–1323. http://dx.doi.org/10.1109/INDIN.2015.7281926.

Rojko, A., 2017. Industry 4.0 concept: background and overview. Int. J. Interact. Mob. Technol. 11, 77–90. http://dx.doi.org/10.3991/ijim.v11i5.7072.

Russell, S., Norvig, P., 1995. Artificial Intelligence - a Modern Approach. Pearson.

Salah, K., Alfalasi, A., Alfalasi, M., Alharmoudi, M., Alzaabi, M., Alzyeodi, A., Ahmad, R.W., 2020. IoT-enabled shipping container with environmental monitoring and location tracking. http://dx.doi.org/10.1109/CCNC46108.2020.9045495.

Selvi, M., Kumar, S.V.S., Ganapathy, S., Ayyanar, A., Nehemiah, H.K., Kannan, A., 2021. An energy efficient clustered gravitational and fuzzy based routing algorithm in WSNs. Wirel. Pers. Commun. 116, 61–90. http://dx.doi.org/10.1007/s11277-020-07705-4.

Slijepcevic, S., Potkonjak, M., 2001. Power efficient organization of wireless sensor networks. 2, 472–476. http://dx.doi.org/10.1109/icc.2001.936985.

Tian, D., Georganas, N.D., 2002. A coverage-preserving node scheduling scheme for large wireless sensor networks. pp. 32–41. http://dx.doi.org/10.1145/570738.570744.

Wang, J., Ju, C., Gao, Y., Sangaiah, A.K., Kim, G., 2018. A PSO based energy efficient coverage control algorithm for wireless sensor networks. Comput. Mater. Continua 56 (3), 433–446. http://dx.doi.org/10.3970/cmc.2018.04132.

Wong, C.Y., McFarlane, D., 2007. Radio frequency identification data capture and its impact on shelf replenishment. Int. J. Logist. Res. Appl. 10, 71–93. http://dx.doi.org/10.1080/13675560600813117.

Wooldridge, M., Jennings, N.R., 1995. Intelligent agents: theory and practise. Knowl. Eng. Rev. 10, 115–152. http://dx.doi.org/10.1017/S0269888900008122.

Wu, J., Yuan, S., Ji, S., Zhou, G., Wang, Y., Wang, Z., 2010. Multi-agent system design and evaluation for collaborative wireless sensor network in large structure health monitoring. Expert Syst. Appl. 37, 2028–2036. http://dx.doi.org/10.1016/j.eswa.2009.06.098.