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# Optimisation of the resource efficiency of food manufacturing via the Internet of Things

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ABSTRACT

The food sector is currently very inefficient due to a large amount of food waste it generates, and the volumes of water and energy used. This problem is aggravated by increasing economic costs and stricter regulations associated with the disposal and treatment of food waste, carbon emissions and wastewater discharge. Because of this, resource efficiency is key to a sustainable food system. In this context, it is essential to reduce food waste, energy and water through transparent and accurate real-time monitoring to be able to understand the real reasons behind their generation/use. Understanding these reasons would help food manufacturers to redesign their processes and achieve operational improvements. The Internet of Things (IoT), a relatively new manufacturing concept within Industry 4.0, can support this. IoT consists of an information technology infrastructure for data collection and distribution, that can significantly influence the efficiency and performance of manufacturing systems. This article presents an IoT-based framework for monitoring the generation of food waste and the use of energy and water in the food sector. The framework supports the identification of improvements to optimise the resource efficiency of food manufacturing through the design and implementation of a number of IoT-based tools.



## 1. Introduction

The food industry is one of the largest manufacturing sectors and a key contributor to the economy (FoodDrinkEurope, 2017). When food is harvested, stored, processed, packed and transported, it consumes vast amounts of resources (i.e. material, energy and water) (Krishnan et al., 2020) and generates vast amounts of food waste (FW) (Garcia-Garcia et al., 2019), which makes the food sector very inefficient (DEFRA, 2006). At the same time, these activities cause negative impacts on the environment due to emissions to air, water and soil. Implementation of lean and green manufacturing practices and resource-efficient processes can help in tackling these issues (Nabhani et al., 2017; Nadeem et al., 2017). Resource-efficient processes offer several benefits to food manufacturing, including cost savings, support towards meeting environmental regulations and increasing the added value by providing more sustainable food products, whose demand is growing by consumers (European Commission, 2016). Specifically, reducing Food waste generation and Energy and Water consumption (FEW) is paramount to improve the resource efficiency of food manufacturing.

In many food factories, resource efficiency efforts are hindered due to the lack of awareness of resource consumption trends (Hill and Scudder, 2002) and FW generation patterns. For instance, food factories may have generic data regarding the amount of resources consumed through their periodical bills, the FW generated, effluent discharge and $CO_2$ emissions. However, they are often not aware of resource use and waste generated at the production-line level, or even down to the machine level (Jagtap, 2019). By collecting and analysing FEW data at the machine level in real time, better management decisions can be made to minimise FEW and thereby to improve resource efficiency.

In this context, the Internet of Things (IoT) can support the real-time monitoring of FEW in the food industry. The IoT has been defined 'as a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies' (ITU-T, 2012). Manufacturers can significantly improve their productivity through the adoption of IoT systems (Daugherty et al., 2015). IoT systems

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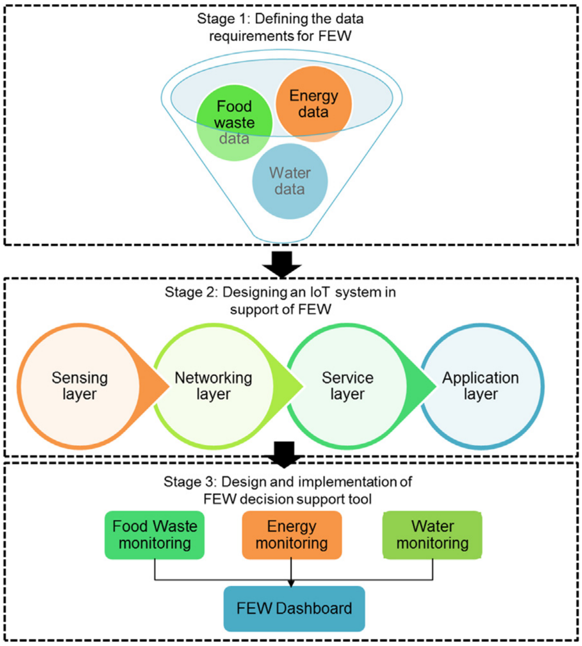


**Fig. 1.** IoT-based FEW framework for resource efficiency in food manufacturing.

have the potential to be used across the whole factory for monitoring FEW and identifying the processes that are less efficient (Holmström et al., 2019). These actions would help the factory management to radically improve the environmental sustainability of their operations. Some food manufacturers have already implemented some IoT-based technologies to collect and analyse FEW data to make resource-efficient food production decisions (Pang et al., 2015).

However, IoT is generally not utilised to its full potential, thereby only leading to slight improvements in operational efficiency. The IoT is often applied with a single objective and to only one actor in the food supply chain. For instance, a majority of its applications in the food industry are restricted to food traceability. Furthermore, IoT implementation is challenging as it needs expertise from the food industry and IoT developers. Besides, food supply chains are complex, food products have varied shelf-life and properties, and they face variable consumer demands. Consequently, many food businesses have not yet implemented IoT as part of their sustainability approach. The current major research challenge is to go beyond the minor incremental improvements and to aim for radical changes by developing IoT-based food factories.

The main aim of this article is to help to improve the overall resource efficiency of the food manufacturing sector through the adoption of IoT-based technologies to monitor FEW and make the information available to the factory management via dashboards. Consequently, environmental considerations can become embedded into the core of the decision-making process leading to improved sustainability of food manufacturing. To do so, this article presents a novel IoT-based framework to optimise resource efficiency in food manufacturing.

## 2. Overview of the framework

This article presents a novel framework to reduce FEW generation/use in the food manufacturing sector via an IoT system. The framework consists of the three stages outlined in Fig. 1, which are briefly described below.

- Stage 1 - Definition of the datasets required for FEW: In this stage, the FEW data that need to be collected is determined. Also, it is necessary to know from where within the food manufacturing processes the data can be extracted and how these data are filtered to obtain meaningful information to support supply chain resource-efficient decisions.
- Stage 2 - Design of an IoT system for monitoring FEW to support resource efficiency: The second stage is to design an IoT system to monitor FEW's current status and patterns. In this stage, it is essential to identify the type of sensors, electronics or other hardware and software systems needed to collect FEW data continuously.
- Stage 3 - Model and design of a FEW decision support tool: In the final stage, the valuable information generated through the IoT system is analysed to produce FEW key performance indicators (KPIs) and reports for better planning of food manufacturing operations. This allows focusing on FEW-intensive operational activities and identify and introduce improvements to manage these resources more efficiently.

These three stages are presented in detail in the remaining sections of this article.

## 3. Stage 1 – definition of the datasets required for FEW

The first stage is to define the type of FEW information that needs to be collected and how the data should be processed. These data allow stakeholders to make informed decisions. The following are the major categories of FEW information to be collected:

1. FW can be categorised into three major categories (WRAP, 2009):
   a Avoidable waste – FW that at some stage before disposal was edible and planned to be consumed (e.g. bread, meat, cheese).
   b Possibly avoidable waste – FW that was edible, but some people would have had consumed and others not due to personal preferences (e.g. apple skins, potato skins).
   c Unavoidable waste – FW that has always been considered inedible (e.g. bones, banana skins, eggshells).
2. Energy can be categorised into two major categories (Seow, 2011):
   a Direct energy – Energy required by various processes to produce a finished food product (e.g. cleaning, washing, chopping, packing, chilling, transporting).
   b Indirect energy – Energy utilised by surroundings in which food production processes are carried out, or food is stored and transported (e.g. lighting, ventilation, heating).
3. Water can be categorised into two major categories (Sachidananda et al., 2016):

a Production water – Water used directly by food production processes. Production water is further divided into two subcategories:
   i Process water, required to convert raw ingredients into finished food products (e.g. washing, boiling, cooking).
   ii System water, to run production machines, tools, and keep an adequate factory environment (e.g. cleaning of equipment, heat exchange).

b Non-production water – Water used by facilities or other utility infrastructures to support production activities, such as heating and sanitation.

Once the type of FEW data has been defined, the sensors must be adequate to collect the data from the equipment. It is important to select the right hardware (sensors and smart meters) and to install them at the right locations (e.g. production area, section, machine). The location for such installation should be decided based on what processes are believed to have the highest impact on FEW efficiency. Following the application of the FEW framework and once sufficient data is collected, evidence would support focusing on the least-efficient processes, as well as identifying at what times such processes perform less efficiently. Once these processes are optimised, hardware can be reinstalled in new locations to further optimise the entire production process, following an iterative step-by-step implementation.

The information collected via sensors and smart meters is stored and analysed using a software at the actor level or stored in the cloud. The results obtained via data analysis are continuously visible to all stakeholders in real time, and if there is an unusual pattern of FEW factory staff can be alerted. The data are summarised within a live resource dashboard, stored, and audited for further analysis in support of future production strategy or process/system reengineering.

The FEW data can be incorporated into planning systems to allow better visibility and faster decisions on planning, scheduling, storing, ordering and other resource management practices. Although the communication between sensors or smart meters and existing planning systems is complex due to interoperability issues, sensors can generate results in different file formats, such as XML, JSON and CSV files (Mäs et al., 2018), which can be used by various operational planning systems, such as Enterprise Resource Planning (ERP) (e.g. Epicor, Solarsoft, SAP, Sage X3) (Compare Business Products, n.d.). These solutions allow factory management to monitor the real time status of FEW.

## 4. Stage 2 – design of an IoT system for monitoring FEW to support resource efficiency

IoT architecture is formed of several layers. A sensing layer (also known as perception layer) communicates with the local server or cloud platform via gateways. These gateways then collect the data, as part of a network layer (also known as communication layer), in a customised or specific IoT format, e.g. message queueing telemetry transport (MQTT) format. Next, the data are transmitted to the local server or cloud platform through wired or Global System for Mobile Communications (GSM) based internet (Al-Fuqaha et al., 2015). Collected data can then be analysed within an application layer and used to explain why and how much FEW is generated/consumed. For example, certain food processes producing an excessive amount of FW can trigger an alert in real time via an Android application to the management, compelling them to take immediate action to reduce FW. We propose an IoT architecture for FEW monitoring in the food sector based on four layers: sensing, network, service and application layers. We have developed and tested these layers, which are explained in the next subsections.

### 4.1. The sensing layer

Sensing devices include cameras, handheld devices, temperature probes and RFID tags, amongst others. To be considered IoT-sensing devices, they need to establish direct or indirect communication with the internet. Arduino or Raspberry Pi connection with Ethernet or Wi-Fi is considered as a direct connection whilst Zigbee or Bluetooth devices connected via Zigbee gateway or mobile phone respectively are considered an indirect connection (Jagtap and Rahimifard, 2019). This subsection describes the requirements for the sensing layer in order to collect FEW data from sensors, smart-meters or other actuators.

#### 4.1.1. Measurement requirements

The required data accuracy and time intervals for data collection and requirements by the food manufacturing company must be considered to select sensors to record FEW data. In some cases, based on the requirements and industrial guidelines, the FEW data could be viewable to designated users in real time. Besides, a detailed report based on collected real-time data can be generated.

We propose a load cell and a combination of load cell and camera to measure FW. A load cell with a calibrated accuracy of ±0.001 kg and a 5 Megapixel camera is used for capturing the image. To measure energy consumption, we propose an off-the-shelf smart meter that uses an Arduino YUN board and a combination of voltage and current sensor. For water monitoring, we propose an ultrasonic smart water meter that uses the Arduino-based Electronic Interface Module (EIM) for both wired and wireless (Wi-Fi) transmission of the real-time date stamped data log on water use.

#### 4.1.2. Sensor node requirements

The sensor nodes selected are long-lasting, needing minimum maintenance, flexible with an open design and able to transmit data wirelessly. Technologies such as Zigbee, Wi-Fi and Bluetooth are adequate for wireless transmission of data. However, in the food industry, due to a production environment with thick-walled stainless-steel equipment and long distances, motors and machines reduced or affected the capability to transmit the data wirelessly. To overcome this issue, short-distance communication technologies such as Near Field Communication (NFC) or Radio Frequency Identification (RFID) can be used. Still, then the opportunity to view the data in real time is hindered. For the FEW systems proposed in this research, a combination of both Wi-Fi and Bluetooth technology was used. The sensor nodes were installed on the factory floor, ensuring minimum disruption to food operations.

#### 4.1.3. Scalability requirements

The proposed IoT architecture could be scaled up to handle a large number of devices that constantly transmit and process data. However, this can be expensive and complex. Therefore, the FEW systems proposed were commissioned on a single production line with a view to potentially replicate to other production lines in the future. The ability to deploy cloud infrastructure is an essential requirement towards elastic scalability, i.e. having an architecture which deploys cheaper servers and supports small as well as large deployments.

#### 4.1.4. Device identity requirements

The device identity stores and permits the authorisation of cryptographic information for device client verification purposes. With regards to FEW monitoring, the devices were identified, paired and secured so that cryptographic information is not disclosed to any unauthorised parties or entities. This also ensures fast and responsive operations. Another important function required for the FEW systems is to create identities for adding new devices and removing existing devices from the system. The device identity function only provides access to authorised areas of the system as and when necessary.

#### 4.1.5. Device provisioning requirements

The IoT device must be identified by the IoT system. For the FEW systems, an Azure-based IoT Hub Device provisioning service is used because it allows successful registration and configuration of devices across several hubs. Device-provisioning systems perform both device registration and device configuration through an Application Programming Interface (API).

### 4.2. The networking layer

The networking layer supports the connectivity of the sensing devices to the service layer. The connectivity is achieved via a gateway and established through various protocols such as Hyper Text Transfer Protocol/Hyper Text Transfer Protocol Secure (HTTP/HTTPS), MQTT or Constrained application protocol (CoAP)

(Yokotani and Sasaki, 2016). HTTP is an easy text-based protocol with many libraries that support it. Nevertheless, for IoT use, the most appropriate protocol is MQTT and CoAP. MQTT is a publish-subscribe messaging system, and since it is based on broker model, it has a small overhead (2 bytes/message) and is designed to support intermittently connected networks. CoAP is a protocol designed to provide a REpresentational State Transfer (REST) application based on HTTP semantics with a small impact. It has a binary approach rather than a text-based approach. CoAP is more focused on client-server rather than a brokered approach.

We propose an MQTT approach because of its wider library support, better acceptability, simpler connectivity, and the possibility to embed into existing data collection and processing systems. Due to its brokered model specifications, MQTT is also beneficial for the IoT devices where they send and receive data to/from the cloud or local server. This subsection describes the requirements for the networking layer to transfer FEW data from the sensors or smart meters to the service layer.

#### 4.2.1. Gateway requirements

The most appropriate sensor node to collect FEW data is the gateway, which can acquire data and transfer it via the internet rather than clustering. Nowadays, a range of options is available for commercial gateways/routers which are compatible with an IoT system. The only hurdle is to provide continuous energy supply to the gateways.

#### 4.2.2. Device connectivity requirements

Devices can be connected directly or indirectly through a field gateway with intelligent capabilities to collect and filter the required FEW data to the backend to support the decision-making process. For FEW monitoring, sensing devices are connected via a field gateway to the local server gateway. The sensing devices used for FEW monitoring are varied and often a combination of short-range communication technology (Bluetooth) as well as wireless Internet protocol (IP) secure connections via the internet. Routers act as a field gateway, and their function is mainly to receive data from sensing devices and transfer them to the local/cloud backend.

#### 4.2.3. Connectivity and communication requirements

In order to address the memory capacity and power requirement of the IoT devices, a small, easy and binary protocol is needed, e.g. HTTP, which provides combined and uniform connectivity. Some of the devices used in FEW monitoring connects directly, and others need a gateway to transmit the data. The devices that need a gateway require two protocols: to establish a connection to the gateway and to establish a connection from the gateway to the cloud or local database. Therefore, the proposed IoT-architecture needs to support the transmission of FEW data and protocol bridging.

#### 4.2.4. Device management requirements

The IoT devices to monitor FEW components need to fulfil certain industrial requirements, including allowing only authorised devices to connect, allowing software updates on devices, erasing the data on misplaced or stolen devices, and allowing remote access to enable/disable/re-configure hardware or network capabilities.

#### 4.2.5. Security requirements

Security is a key aspect of IoT devices since they are directly or indirectly collecting highly confidential data and bringing it to the internet. Risks could include:

- Flaws in the internet system which IoT designers are not aware of leading to breach of data
- Flaws with the IoT devices
- No safety breach of data, for instance, from rogue sensors or actuators

In order to address these risks, the following actions were implemented:

- Blocking or disabling open ports in IoT devices
- Avoiding IoT devices that do not support asymmetric encryption
- Identifying hardware that is easy to decode through reverse engineering
- Identifying poor practices with regard to identity and access to management

### 4.3. The service layer

The service layer aggregates, analyses and brokers communications. This layer supports the MQTT broker to communicate to the devices, collects and combines data from various sensing devices and acts as a transformation medium between various protocols. The service layer also collects, stores and process the data, and can even warn and serve based on the information collected. To monitor FEW data, the service layer should have the following requirements:

- Ability to handle a large increase in transactions
- Support data storage for all the data generated in a column-based data storage
- Complex data processing in real time, send alerts and take actions based on data analysis
- Support different platforms, e.g. Java, PHP, Ruby or Python

This section describes the requirements for the service layer to process FEW data once it is received from the networking layer.

#### 4.3.1. Storage requirements

FEW-related activities usually generate large volumes of data, depending on how many connected devices generate data, how frequently they send data and the file size of the data sent from those devices. FEW data are often time-stamped and stored so that they can be visualised and used for generating reports and retrieved later for further processing. These data are often classified as warm or cold data stores. Warm data storage is recent data, i.e. a day, week, or month of data that can be retrieved with low latency. Cold data storage is typically historical data with higher latency. Cold data storage is used less often but may be important for future reporting, analysis or machine learning applications. For FEW monitoring purposes on a daily or monthly basis, warm database storage is used. FEW data that is over a month old can be stored in a cold data store as it will not be subjected to low latency, high volume like the warm data store.

#### 4.3.2. Cloud or local database requirements

On-line monitoring of FEW requires continuous collection and processing of data in the cloud or the factory's local servers. However, the vast data generated by sensors could be too overwhelming for local servers and, therefore, cloud resources are preferable for FEW monitoring. Clouds reduce the amount of energy consumed for running the servers and provide data analysis with computing capacity. The cloud has the capability to process both continuous and batch data generated by nodes and gateways as well as provide efficient Big Data execution frameworks such as Spark and MapReduce.

#### 4.3.3. Data flow and stream processing requirements

The volume of FEW data generated may affect the flow of data processing. Depending on various scenarios and applications, data

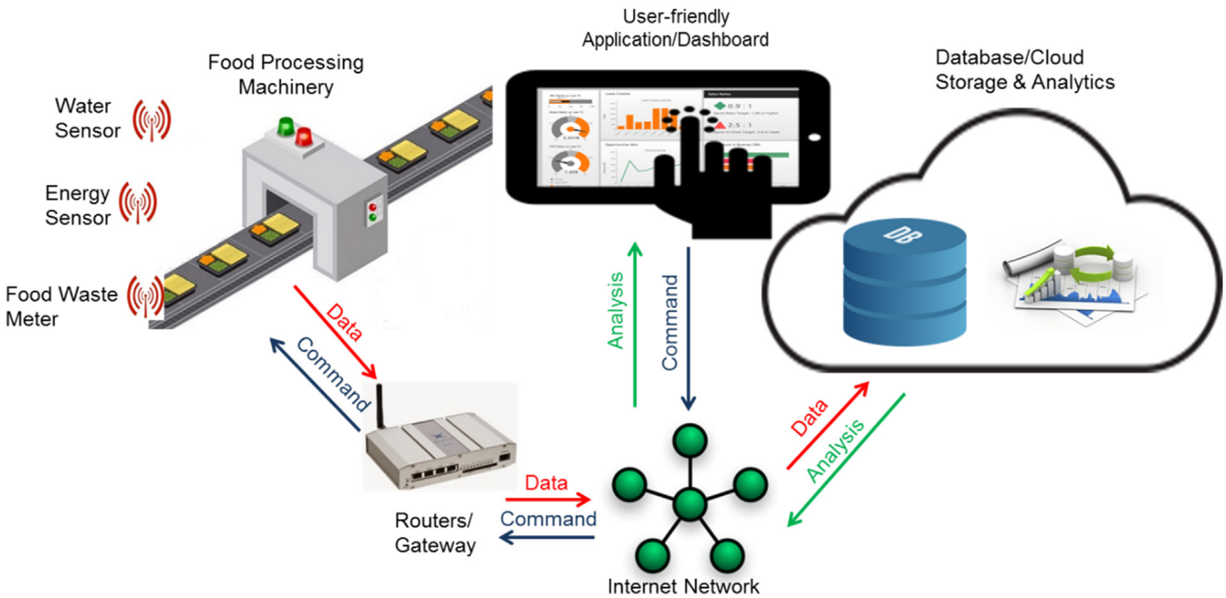


**Fig. 2.** FEW monitoring systems.

can flow through different steps, stages, formats and orders. Data are mostly processed by simultaneous corresponding tasks. For FEW monitoring, these tasks can be categorised in the following:

- Storing FEW data in permanent archives, temporary files or memory caches
- Routing FEW data to transfer data to storage databases, analytical processes and actions
- Analysing FEW data to run through data records via set parameters to generate various output data records

These processes can be combined to show FEW information in real time in dashboards. The proposed architecture considers the fact that food business would run a number of corresponding data stream processors, either by segregating or by forwarding data to multiple channels.

#### 4.3.4. Data collection, analysis and actuation requirements

IoT devices have some kind of User Interface (UI) design and collect data from one or more sensors or actuators or a mix of both. The collected data are stored, analysed and then an appropriate action is taken. The proposed IoT architecture for FEW monitoring is designed to support a large number of devices that generate a continuous stream of data. Therefore, the architecture must be able to handle a varied and high volume of data. It should also process the data in real-time.

#### 4.3.5. Topology and entity store requirements

Business logic, device and application models are required to build FEW applications. The business logic can include the process of defining and configuring business rules, executing searches for a set of devices, building a user interface and dashboard to ensure uniformity through the various components of the IoT solution and backend systems. The topology and entity store consist of a database that is comprised of FEW application entities and relationships within the entities. It further provides descriptive information about entities and provides rich, or irregular index competences with the aim to offer immediate lookups.

### 4.4. The application layer

The application layer supports the IoT-sensing devices to interact outside of the device-focused system. For the FEW monitoring systems, there is a need to build a web-based front-end portal that networks with devices and data processing. Machine-to-machine communication can be used to interact with external network systems. For the proposed IoT architecture, the approach is to build the web front that deploys a modular front end, e.g. a portal. This action allows easy and quick configuration of useful User Interfaces (UIs). The proposed architecture is able to support web server-side technologies, e.g. Java, Python, PHP and Ruby. Finally, FEW dashboards show relevant graphs from the FEW data obtained from the devices and data processing. This section describes the requirements for the application layer to display the FEW data in a user-friendly dashboard.

#### 4.4.1. User-side interface requirements

The user-side interface of the IoT infrastructure's is continuously adapted depending on the complexity of the food product and the end-user requirements. For FEW analysis, energy and water measurement systems were not altered. For complex FW, with many ingredients, software supported by human intelligence is needed, and in this case, factory operators identified the type of FW and reasons for its generation. For single ingredients or less complex FW, image-processing technology and software made the waste monitoring system fully automatic and independent from humans.

#### 4.4.2. The solution user interface (UI) requirements

The solution UI usually consists of a website and reporting. This could include a mobile app, desktop app or web service to provide access and visualisation of data collected, analysis of results and notification of alerts and alarms. Regarding the FEW solution user interfaces, it provides live, shared and interactive dashboards, appropriate to visualise the IoT system with large numbers of connected devices.

#### 4.4.3. Monitoring requirements

The IoT monitoring system is used to determine whether the provided solution works, so the devices or systems are correctly configured to generate accurate FEW data. Visualisation of monitor-

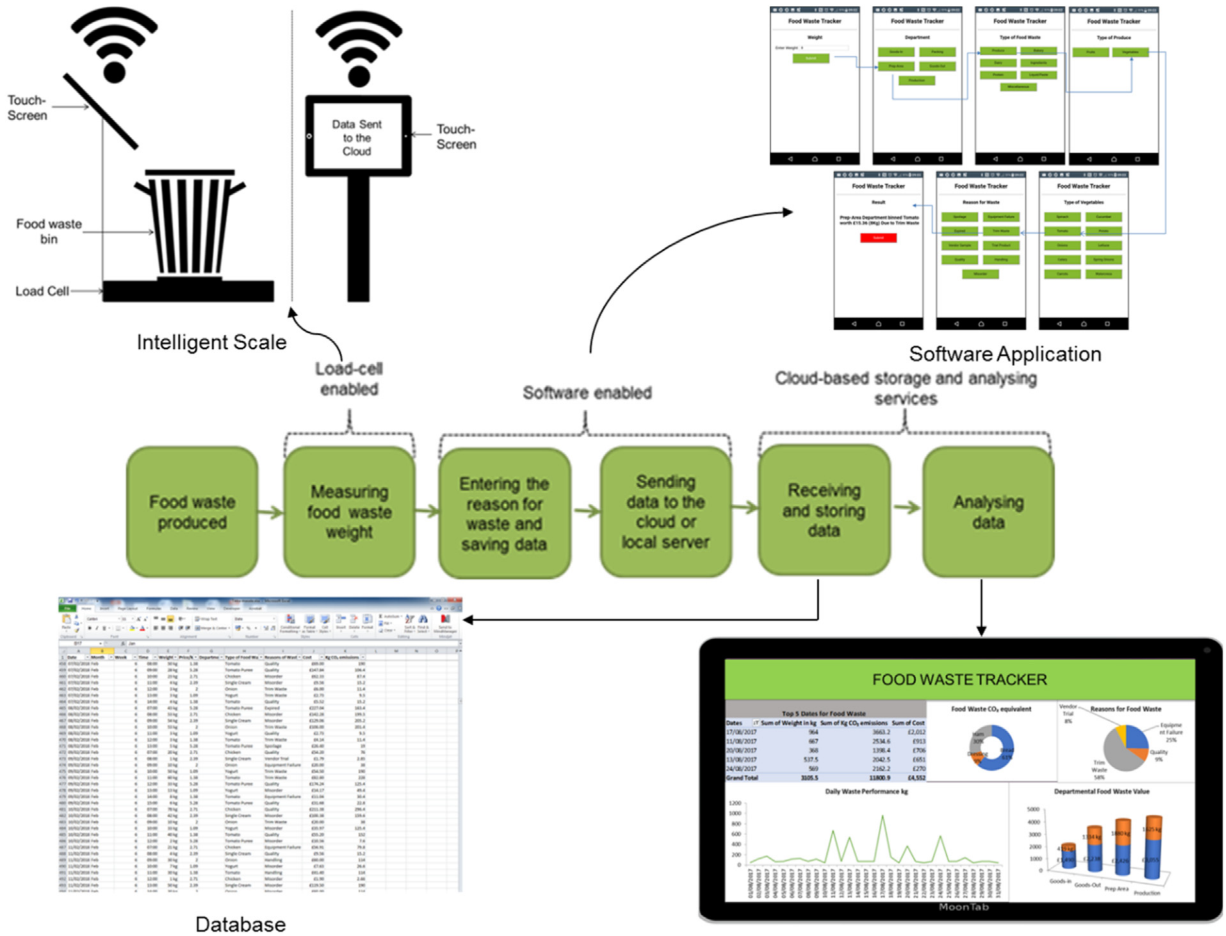


**Fig. 3.** IoT-based FW tracking system (Jagtap and Rahimifard, 2019).

ing standards provides insight into the robustness and performance of the FEW systems and alerts business stakeholders to any deviations from set parameters to facilitate immediate response.

## 5. Stage 3 – model and design of IoT-based FEW decision-support tools

To support the minimisation of FEW, the food-production equipment must be fitted with FEW sensors or meters, which transmit data via gateways and internet networks to database storage, as depicted in Fig. 2. The stored data is analysed and displayed in a dashboard to support making informed real-time decisions.

The FEW monitoring systems proposed in this research consist of the following three sections: an intelligent scale and image-processing unit for FW monitoring, commercial sensors/smart meters for energy monitoring, and meters with ultrasonic technology for water monitoring. These three sections of the FEW monitoring system are explained in the following subsections.

### 5.1. FW monitoring

The FW monitoring module is used to collect and process the data related to solid FW generated on the factory floor. The data can be collected via an intelligent scale or an image processing unit, as explained in detail by Jagtap and Rahimifard (2019) and Jagtap et al. (2019a).

The use of an intelligent scale for FW monitoring includes six steps (Fig. 3): FW collection, FW weight measurement, entering the reason for FW generation via a bespoke software, sending data to the cloud or local server, data store, and data analysis. The architecture of the intelligent scale includes four layers (Fig. 4): the sensing layer, the network layer, the service layer and the application layer (Jagtap and Rahimifard, 2017). The sensing layer uses load-cell technology to weight the FW and a software application operated via a touchscreen to input the reason for FW generation. In the network layer, the data are transferred to the service layer via Bluetooth technology using hardware such as Arduino UNO, HM-10 BLE Breakout and Linkit ONE. In the service layer, the data collected are stored locally or in the cloud and analysed. In the application layer, the data are presented in a FW dashboard.

An automated image processing unit, like the one depicted in Fig. 5, can also be used for FW monitoring. While food products travel on a conveyor belt, a camera photographs them and load cell the measures their weight. The information is sent to the control computer. If a product visually imperfect is detected, a rejecter arm segregates the product. The architecture of the automated image-processing unit includes four layers (Fig. 6). The sensing layer collects the image and weight information via the camera and load cell. The network layer sends it to the service layer via Bluetooth or wired hardware. The images, weight, time and date are recorded in the service layer. The data available in the service layer is then presented in a dashboard via the application layer.

### 5.2. Energy monitoring

The energy monitoring system is used to collect and process energy-use data within the factory. Sensors and smart meters

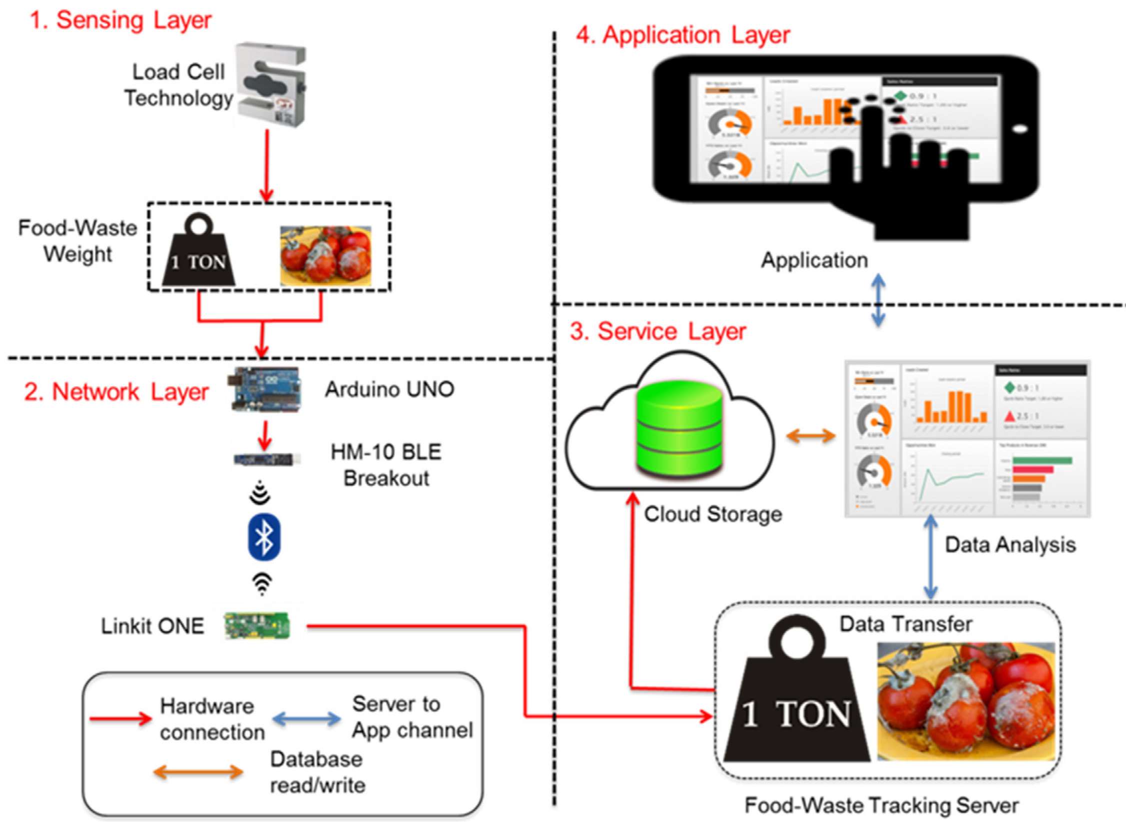


**Fig. 4.** The architecture of the intelligent scale (Jagtap and Rahimifard, 2019).

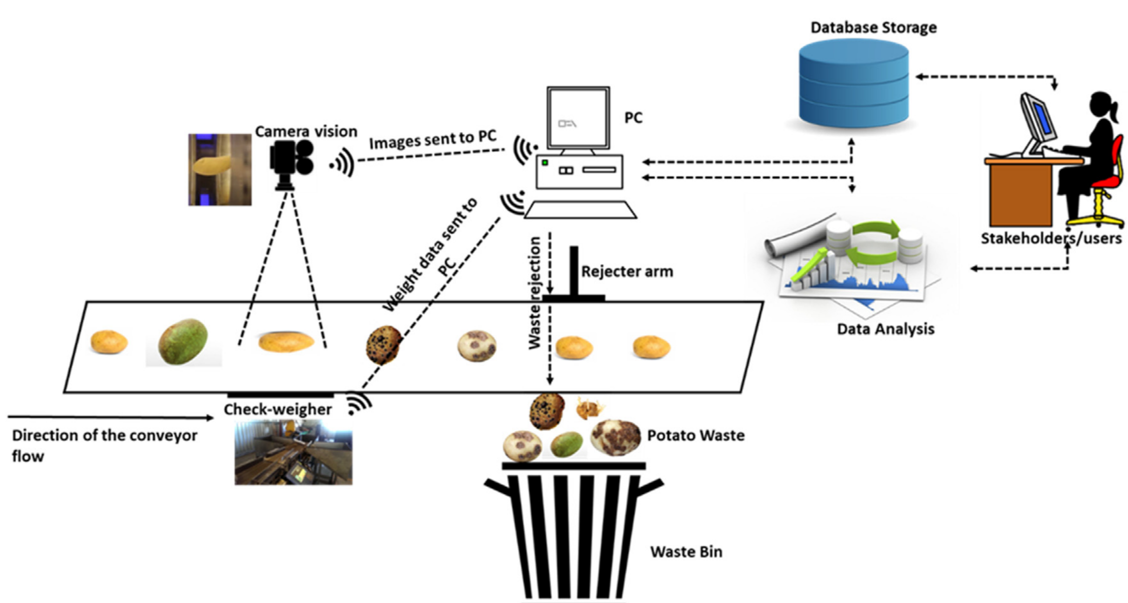


**Fig. 5.** Automated potato waste monitoring system (Jagtap et al., 2019a).

supported with the software are used to record the energy-use data. The analysis of the energy data can lead to the following:

- Reduction in the total energy usage of the equipment when idle and non-value-added activities
- Identification of irregularities in production activities based on the sudden surge in energy use
- Track machine performance to monitor its maintenance and plan repairs in advance
- Record the energy used in the manufacturing operations as part of environmental reporting
- Highlight any inconsistent deviations or patterns caused due to excessive energy use

Most energy sensors and smart meters commercially available can collect energy data and have their own software to process the

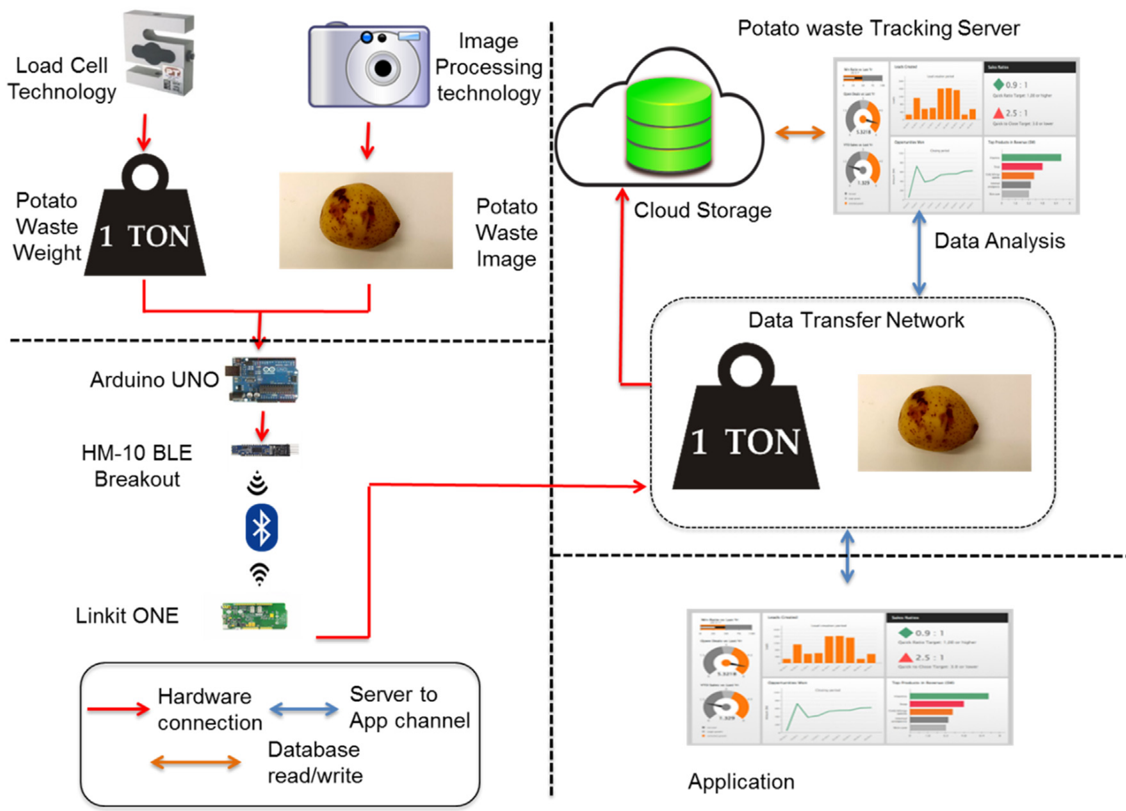


**Fig. 6.** Architecture of the automated image processing unit (Jagtap et al., 2019a).

collected data. We used an OWL intuition -Ic standard energy monitor network to transfer data via a wireless network to the controller PC. The energy smart meter uses current transformer sensing technology to sense and monitor a magnetic field around the electric cables. It assesses the electric current using either the Standard (up to 71 Amp) or Large (up to 200 Amp) sensors. This information is then directed from the transmitter via a radio frequency of 433 MHz, which has a range of up to 30 m. The information is then processed and multiplied to a fixed voltage to calculate the quantity and cost of energy used. The generated information is continuously transmitted and stored in a local drive in text format. The software collects energy data such as energy consumption, peak consumption periods, cost of energy consumption, timings and $CO_2$ emissions of energy consumed.

Fig. 7 gives an overview of the daily electricity consumption, cost of energy consumed, and $CO_2$ emissions associated with energy use. Fig. 8 gives details of any energy peaks observed during the day.

### 5.3. Water monitoring

The IoT-based water monitoring system helps in identifying leaks and water wastage. Fig. 9 shows an IoT-based architecture for water monitoring. The sensing layer (bottom right quadrant) collects data on water flow rate and water quality in real time via sensors, e.g. pressure transducers, flow meters and water quality sensors. The networking layer (bottom left quadrant) reads sensors and devices. It executes basic functions of linking up the sensing layer to the database systems and software platforms via short-range wireless networks such as Wi-Fi, Bluetooth, RFID and ZigBee. The service layer (upper left quadrant) manages data, software applications and platforms. It collects information from all IoT-gateways, processes it, sorts it and stores it in a data warehouse. The stored data is made available for data mining and analysing by applications running in the cloud. The application layer (upper right quadrant) performs real-time water data analysis, generates water reports and presents information to the user over the internet via HTTP. The web application is powered by ASP,. NET, HTML5. It supports user-friendly functionalities such as diverting water from certain food production processes to other secondary processes (considering the water quality), checks the water use, sends alerts and allows viewing historical data.

Water smart meters are widely available in the market. We used a FLUID water meter for measuring water flow rate, which uses ultrasonic technology to capture the water flow through a pipe. Therefore, there is no need for cutting or adjusting pipes to install the water meters. The device is clamped around the pipe and connected to a Wi-Fi network. It transfers the water consumption data via a Wi-Fi network and sends it to the cloud storage. After data analysis, the information is sent back to the user and displayed in a dashboard.

### 5.4. FEW dashboards

The collected data on FW, energy and water are combined to build the FEW dashboards. The dashboards show the values of the most relevant key performance indicators (KPIs) for FEW monitoring. It is capable of storing and displaying FEW data at departmental, line or machine-level. In this way, the FEW dashboards can support stakeholders to make informed decisions based on the FEW. For example, they can help identifying hotspots where FW generation, water use and/or energy use are particularly high. Next, the reasons for such high values must be identified, followed by taking an action to minimise them. These actions could be, for example, reducing the temperature of overheated ovens to minimise overcooked food, fixing water leaks or improving thermal insulation for some equipment. An example of a particular moment of FEW

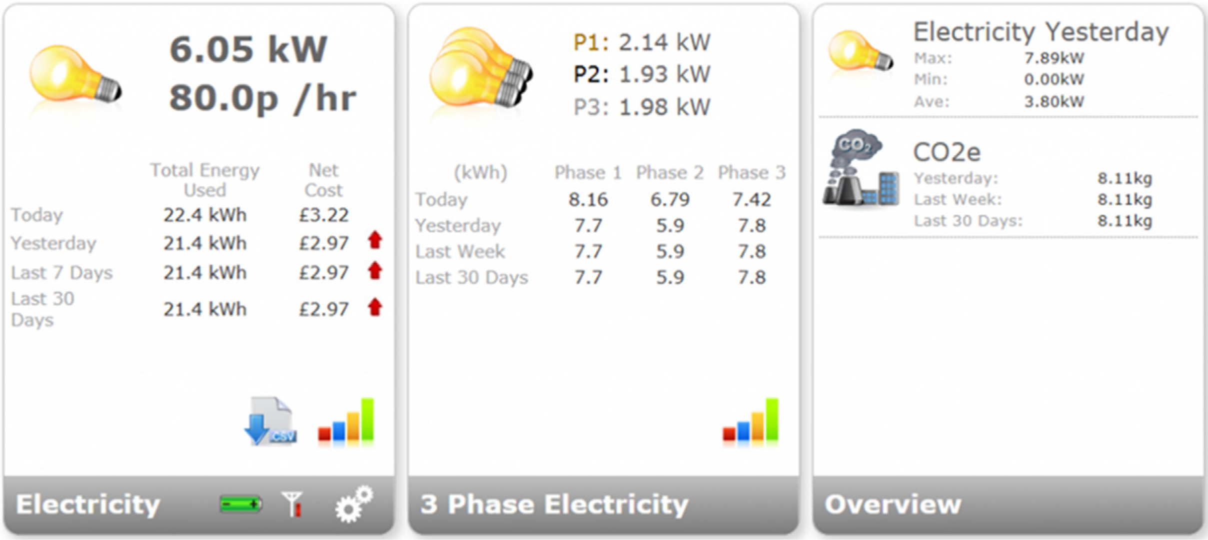


**Fig. 7.** Cost, daily consumption and $CO_2$ emissions.

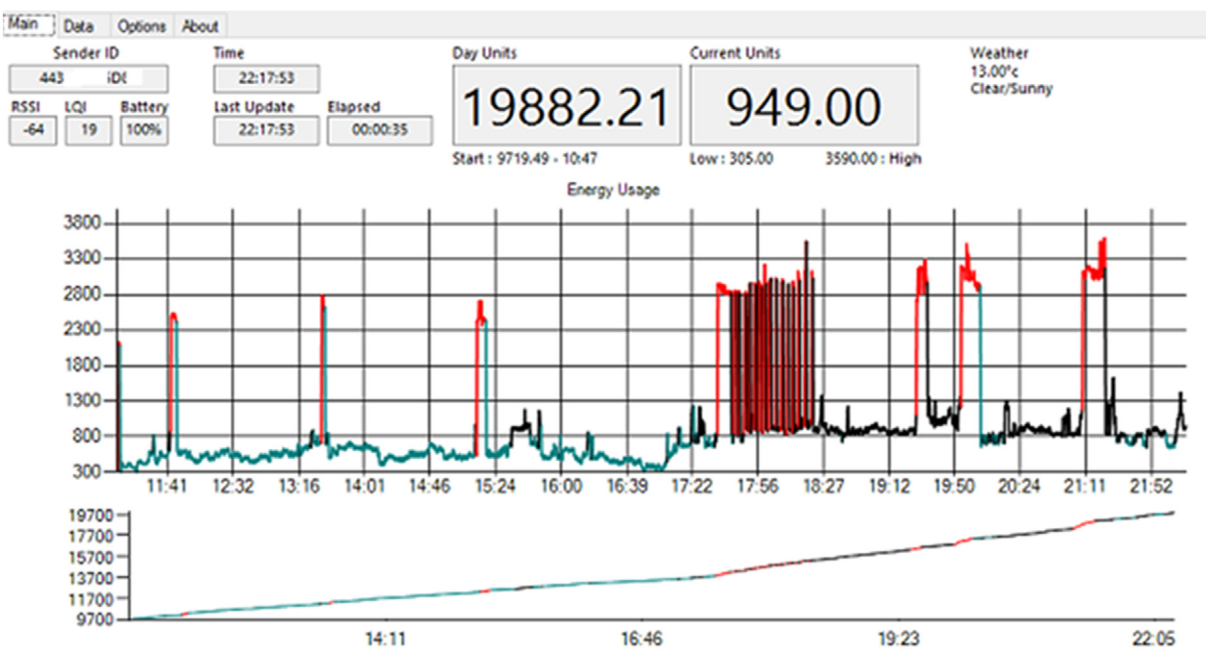


**Fig. 8.** Day energy graph.

monitoring in a food manufacturing company displayed in the FEW dashboards can be seen in Fig. 10.

Fig. 11 shows the decision-support process for improving resource efficiency in food manufacturing. The real-time FEW data are collected by means of IoT technologies, then stored in the cloud or a server and finally analysed to extract useful information. Data analytics is used to assess the FEW generation/consumption. The information created can be integrated into food production management systems and tools that support optimising the efficient use of resources, for example, by using decision support systems (DSSs), KPIs and automated dashboards. The information obtained from the data analytics can finally support strategic, operational and control decisions in food management systems.

Food manufacturing decisions can be made on strategic, operating and control levels. These decisions allow more resource-efficient production activities when FEW data are used.

At the strategic level, decisions about products, processes and facilities are undertaken. This includes developing long-term production plans, process design, selecting and managing production technology, planning the arrangement of services and planning for the optimal distribution of resources amongst machines, product lines and departments. The improvement of resource efficiency can be achieved by more efficient food processing, good manufacturing practices or the redesign of food manufacturing processes.

Operational management focuses on food production and meeting customer demand. This involves aggregate planning, production scheduling, planning and controlling finished goods inventories, planning materials and capacity requirements. It also includes short-term decisions about what and when to produce. FEW data from a particular food processing allows the machine user to identify the most efficient solution. This information, when fed into the production scheduling systems, can reduce FW generation as well as energy and water consumption.

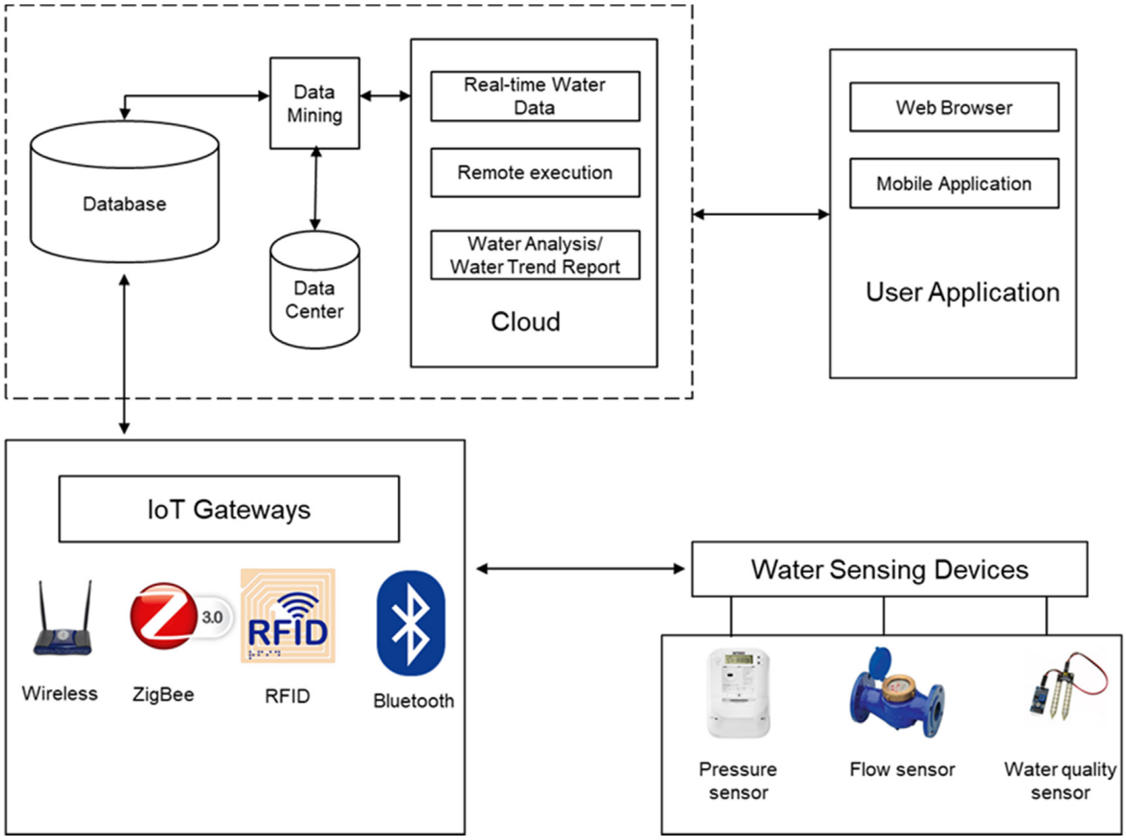


**Fig. 9.** IoT architecture for water monitoring (Jagtap et al., 2019b).

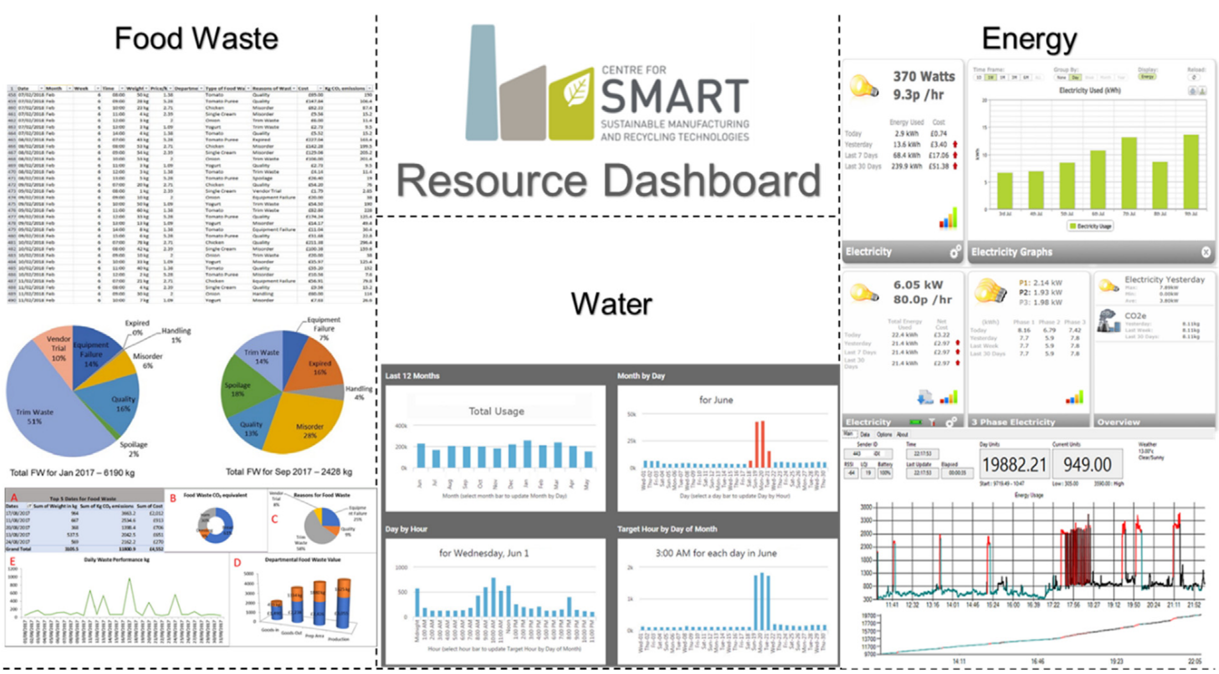


**Fig. 10.** FEW dashboards to improve resource efficiency in food manufacturing.

In production planning and control decisions, the focus is on managing food operations, for instance, the planning for the efficient utilisation of human resources in operations, controlling the quality of food products and services, and maintaining the machines and facilities.

## 6. Discussion

In recent years, food manufacturing companies are facing various challenges such as unpredictable demands and frequently changing customer and supplier requirements. New technological

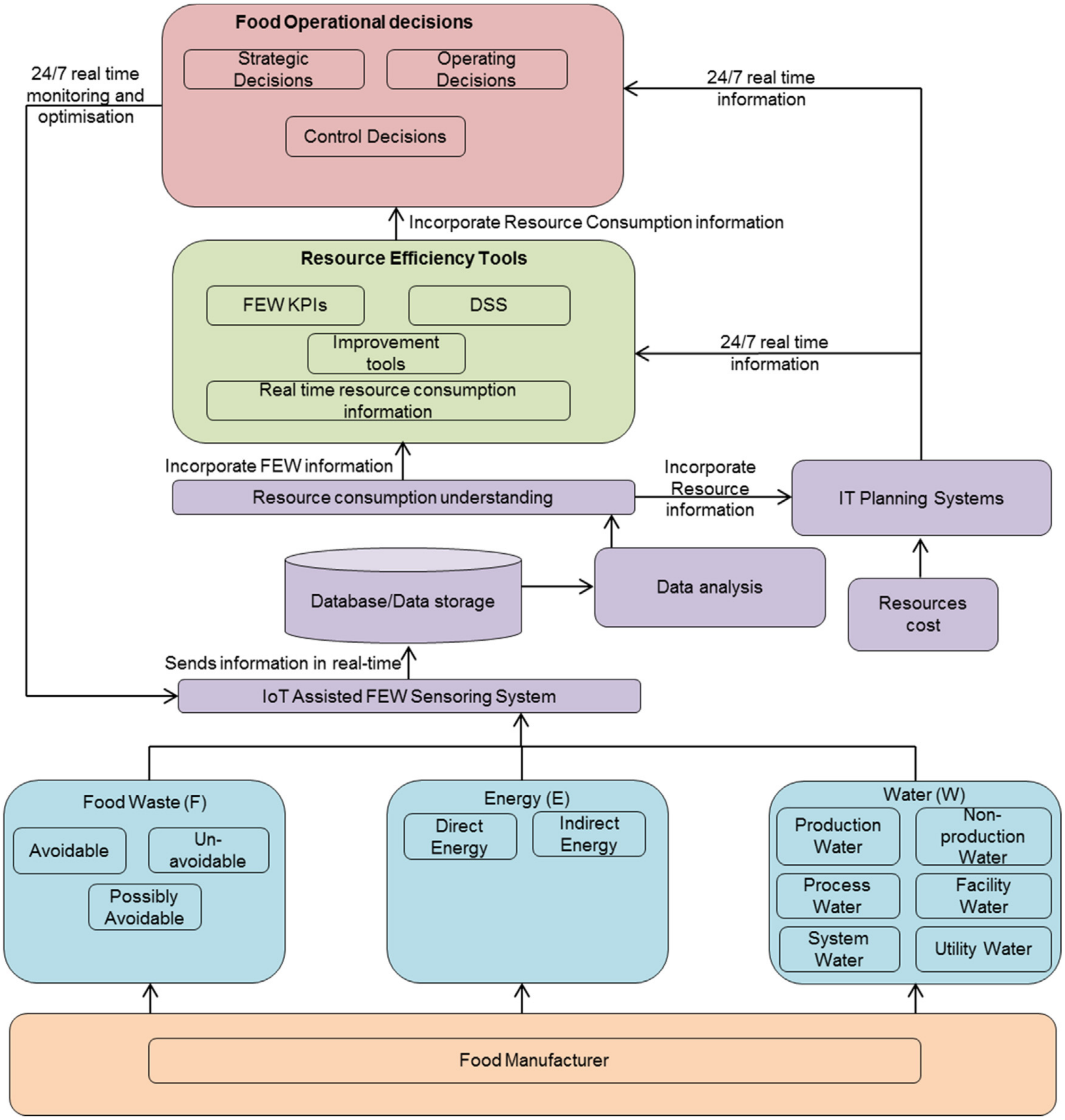


**Fig. 11.** Decision-support process for improving resource efficiency in food manufacturing.

concepts such as IoT and Industry 4.0 are being embraced to address these challenges. Industry 4.0 is a complex but flexible system which can provide advantages such as improving quality, efficiency and competitiveness. The food sector can be considered to be more demand-driven than supply-driven, meaning that consumers dictate manufacturers what and when they want to consume. In order to address this demand, the equipment and manufacturing systems within the food factory should be able to share information and control each other autonomously making the whole process more resource efficient. The digitalisation within Industry 4.0 can support food manufacturers with process redesign, development and improvement. The availability of accurately measured real-time FEW data can help food manufacturers to become more resource efficient, improving their environmental performance and reducing economic costs.

The wide range of hardware and software discussed in this article highlights that there is a need to identify key FEW data and hotspots within the production line since the collection of data for all processes is generally unfeasible. Moreover, a systematic plan for the use of data collected is also needed. The digitalisation of FEW data within food manufacturing can offer substantial environmental and financial benefits. Often, this approach is not followed by food manufacturers due to their reliance on traditional paper-based systems. We believe some of the advanced technologies based on IoT and Industry 4.0 can bring real-time transparency and visibility as well as efficiency to manufacturing processes. Having access to real-time FEW data of key processes would be very valuable to identify the most relevant issues that hinder resource efficiency.

However, the acceptability of these novel technologies in food manufacturing is still small due to many challenges such as setting-up costs, availability and accessibility to relevant skills, and concerns regarding data sharing and security. Another potential issue is burden shifting, which would occur if the efficiency of some processes is improved via the utilisation of the IoT-based FEW framework, but the overall efficiency is decreased due to use of the new devices installed. Clearly, the use of such devices should not increase food waste generation nor water use; however, these devices have energy (electricity) requirements that could exceed energy savings. Although these devices generally need little energy to operate, in comparison with equipment with moving parts (e.g.

conveyor belts) or processes that use large amounts of heat (e.g. ovens), it is important to calculate the overall efficiency improvements that the framework offers. The energy use of such devices can be easily calculated with their time of use and power in use (which should be found in its manual). This must be done on a case-by-case basis.

Therefore, food factories need to undertake a holistic review of the long-term benefits of utilisation of digital technologies to optimise their resource efficiency. It is expected that other stages of the food supply chain could also benefit from the adoption of such technologies to improve their environmental and economic performance, for instance during cultivating, harvesting, transportation and storage.

## 7. Conclusions

The contribution of this research is the following:

- Defining a stepwise framework to improve the resource efficiency of food manufacturing through the design and implementation of a number of IoT-based tools for monitoring and reduction of food waste generation as well as energy and water consumption (FEW).
- Introduction of a new, faster and reliable digital approach to monitoring FEW as compared to the traditional paper-based systems.
- Development of a prototype decision-support system consisting of relevant hardware and software elements to demonstrate the collection and utilisation of FEW data to analyse and optimise processes within a food manufacturing system.

Our framework consists of three stages. Firstly, the definition of datasets required for FEW in food manufacturing. In this stage, FEW data that needs to be collected, stored and analysed were identified. Secondly, the design of an IoT system for monitoring FEW to support resource efficiency. In this stage, the most appropriate sensors, electronics and other hardware and software needed to collect FEW data were determined. Four IoT architectural layers were proposed for collection and analysis of FEW data. Finally, the third stage involved modelling and designing a FEW decision support tool for monitoring FW, energy and water consumption in food manufacturing.

The four IoT architectural layers for FEW monitoring are sensing, networking, service and application layers. The sensing layers consists of all the sensors used to collect data. The collected data is then transferred to the service layer via the networking layer. The application layer includes a dashboard where the users can view key FEW data and make decisions to reduce them. The FEW monitoring systems were designed to be user-friendly and easy to use, so staff with little training can operate it.

In order to collect FEW data, hardware such as a load cell (weighing scale, checkweigher), tablet, vision system (camera), rejecter arm, microcontroller, PC, Arduino/Raspberry Pi, and Bluetooth module were used. The software developed is able to process large amounts of FEW data in real time. Two main approaches for FW reduction were considered: an intelligent scale and an image-processing technology. The intelligent scale needs human support to record complex-FW data, whereas the image processing technology is fully automated and mostly suitable for single-ingredient FW. For water and energy, smart meters and commercially available software were used.

The increasing environmental and economic ramifications related to FEW in food manufacturing activities clearly indicates the need for more efficient use of resources. The adoption of new digital capabilities and readiness of the food manufacturing sector to considerably reduce FEW plays a vital role in the long-term sustainability of food production activities. The fundamental conclusion derived from this research is that the complexities associated to environmental sustainability, costs of food production, national and international regulations, as well as consumer preferences and dietary requirements necessitate the use of automated data collection and associated decision support to sustain the demands in future food supply chains. In this context, the food sector must embrace the emerging concepts introduced by the fourth industrial revolution, i.e. Industry 4.0, to optimise their resource efficiency.

## CRediT authorship contribution statement

**Sandeep Jagtap:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Visualization. **Guillermo Garcia-Garcia:** Validation, Data curation, Writing - original draft, Writing - review & editing. **Shahin Rahimifard:** Conceptualization, Methodology, Resources, Supervision, Project administration, Funding acquisition.

## Declaration of Competing Interest

The authors report no declarations of interest.

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