Managing the food supply chain in the age of digitalisation: a conceptual approach in the fisheries sector

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abstract

In the food supply chain, digitalisation is a process that can have a major impact at the point of origin/point of capture. In order to study the process of digitalisation, this work proposes a two-layer conceptual approach applicable to the fisheries sector. The conceptual approach has a sensor layer where wireless sensor network (WSN) theory is used to model the associated energy consumption of a network of sensors. In the analytics layer, data collected from sensor readings associated to ocean monitoring are analysed using time series. A case study in the fisheries sector is used to illustrate the proposed approach where WSN theory is evaluated based on its applicability to oceanic observation buoys equipped with sensors. Then, a large dataset generated from ocean buoys readings is analysed using time series/scatter diagrams to identify trends and patterns involving snow crab catch conditions. The proposed approach can be seen as a tool that can assist in the management of the supply chain and the adoption of more efficient practices in the fisheries sector which is experiencing a process of digitalisation characterised by the adoption of Internet of Things (IoT) solutions to monitor product history and provenance tracking among others.

Keywords: Supply Chain Digitalisation; Internet of Things (IoT); Food and Perishable Goods Supply Chain; Fisheries sector; Wireless sensor network; Time-series analysis

1. Introduction

Digitalisation of operations and supply chains can be seen as a new paradigm that offers new opportunities. At the moment there is an ongoing proliferation of enabling information technologies developed to assist modern day operations. Xu et al. (2018) indicated that many applications require a combination of recently emerging new technologies, which is giving rise to innovative concepts enabled by technologies comprising cyber-physical systems, Internet of Things (IoT) and cloud computing. Hence, in such environment, sound management practices require the use of tools and frameworks to manage the supply chain.

It has been acknowledged that IoT is a new Information Technology (IT) revolution providing a paradigm shift in several areas including supply chain management (Ben-Daya et al., 2017). The future of the Internet will consist of heterogeneously connected devices that will further extend the borders of the world with physical entities and virtual components (Li et al., 2015). Advances in sensor technology and ubiquitous broadband communication have set the foundation for IoT. In the IoT paradigm, many of the things that surround us will be on the network in one form or another (Gubbi et al., 2013). Xu et al. (2014) stated that the integration of sensors/actuators, radio-frequency identification (RFID) tags, and communication technologies serves as the foundation of IoT and explained how a variety of physical objects and devices around us can be associated to the Internet and allow these objects and devices to cooperate and communicate with one another to reach common goals. By 2020, companies will be spending about £250bn a year on IoT, with half of all that spending coming from the manufacturing, transport and utility industries (Financial Times, 2017). The emergence of the Industrial Internet of Things (IIoT) poses a large impact on established business models of manufacturing companies (Kiel et al., 2017). Furthermore, the relation of IoT with emerging paradigms such as Industry 4.0 has been fully recognised (Fatorachian and Kazemi, 2018).

It is precisely advances in sensor technology that have enhanced the capability of IoT-solutions to meet the needs of the supply chain in multiple industries. Nonetheless, a growing network of sensors can be challenging in terms of data management and energy consumption. Wireless Sensor Network (WSN) Theory seems like a suitable solution to the challenges faced by IoT-solutions relying on the use of sensors for readings/data collection. WSN is a theory that has been employed to collect data about physical phenomena in various applications such as habitat monitoring, and ocean monitoring, and surveillance (Chi et al., 2014). Kelly et al. (2013) highlighted that ubiquitous connectivity has been made possible by advancements in WSNs and it can be considered as one key smart sensor technology that is driving the future of IoT. Moreover, according to Chi et al. (2014) data collection is the essential application of WSN and more importantly it is the foundation of other advanced applications in IoT environments. The same researchers stated that since IoT is associated with a large number of wireless sensor devices, it generates a large amount of data.

In particular IoT relying on the use of sensors for readings/data collection can have a significant impact on the food supply chain. According to Li et al. (2015) today's food supply chain is extremely distributed and complex; it has large geographical and temporal scale, complex operation processes, and large number of stakeholders. In their view complexity has caused many issues in the quality management, operational efficiency, and public food safety. In the supply chain of food and perishable goods, the use of sensors and other IoT-enabled devices plays a major role in terms of generating readings of the conditions pertaining the goods being transported. Among the myriad types of supply chains available in the food industry, perhaps the fisheries sector has the potential to receive significant benefits from the growing adoption of IoT solutions comprising the use of sensors for readings/data collection. In fish and seafood products, increased traceability could be used to provide more information and transparency for the individual discrimination of products and to ensure product quality and compliance with health and safety standards (Schroder, 2008). Fisheries represent a major economic activity. According to the Food and Agriculture Organisation of the United Nations –FAO- (2018) global fish production reached its peak at about 171 million tonnes in the year 2016, with aquaculture representing 47% of the total (53% if non-food uses like reduction to fishmeal and fish oil are excluded). The fisheries sector deals with critical issues such as freshness and waste. This has been addressed by researchers like Mbarki et al. (2009) who pointed out that pelagic fishes represent the main Mediterranean fisheries in terms of quantity. They indicated that waste and spoilage of pelagic fish are considerable because of their high perishability and the lack or inadequate supply of ice and freezing facilities. In this type of scenario which can be found in many fisheries around the world, IoT-enabled devices can be used to monitor and register any variation in transportation and storage conditions.

Food production and food supply chains are continuously affected by weather conditions. In agriculture, changes in weather patterns can have negative effects as Tol (2018) identified crops hit by worsening drought and crops growing faster because of carbon dioxide fertilisation. In fisheries and seafood, weather conditions and current status in the sea determine the distribution of sea fisheries (Taylor, 2006). This is highly relevant as in littoral zones different commercial species of fish can be found if waters are warm, lukewarm or cold. In the era of digitalisation of food supply chains, the use of IoT-enabled sensors for readings/data collection of weather conditions for a specific geographic area can give the possibility of accessing large and accurate datasets that can be analysed for the benefit of planning and operations in the fisheries sector.

The collection of high volumes of data/sensor readings from IoT-enabled devices will require the use of analytics, hence the need to use a comprehensive approach to analyse large datasets. Predictive analytics are suitable to the analysis of large datasets, these involve the use of mathematical algorithms and programming to discover explanatory and predictive patterns within data (Wang et al., 2016). The aim of predictive analytics is to accurately project what will happen in the future and provide reasons as to why it may happen and because of supply disruptions, predictive analytics tools are essential to design supply chain flexibility into logistics operations (Wang et al., 2016). Time series analysis is one of the most accepted methods that can be used in predictive analytics. Time series analysis encapsulates various methods used in the analysis of time series data for the purpose of extracting meaningful statistics and other characteristics of the data (Li, 2018). Time series forecasting is the use of a model to predict future values based on previously observed values (Li, 2018). The use of time series analysis can be found in specialised cases in the food sector involving for example growing non-food crops in marginal lands (Longato et al., 2019).

This paper proposes a two-layer conceptual approach comprising a sensor layer where wireless sensor network (WSN) theory is employed to model the associated energy consumption of a network of sensors that can be used to collect various parameters. In the analytics layer, data collected from sensor readings are analysed to identify trends and patterns based on time series analysis. This work uses a case comprising the fisheries development agency in Atlantic Canada to illustrate the proposed approach. The case involves the point of origin/capture of the supply chain of crustaceans (e.g. snow crab) which is used to illustrate the proposed approach where WSN theory is evaluated based on its applicability to oceanic observation buoys equipped with sensors. A large dataset of just over 10,000 records generated from ocean buoys readings for the years 2016, 2017, 2018 and 2019 is analysed using a Python-written routine for the purpose of performing a time series – scatter analysis. This can enable the identification of trends and patterns involving snow crab capture conditions based on parameters including average sea surface temperature and air temperature as well as further considerations like fishing/capture dates and catch allowances. Point of origin/capture is an important stage as the conditions recorded there can have implications downstream in the supply chain involving transportation, handling storage, tamper proof checks, product history and provenance tracking. The next section provides a literature review of the elements used in the development of the proposed conceptual approach.

2. Literature review: theoretical background about IoT and emergent technologies

Digitalisation has been acknowledged as one major flexibility driver that derives from new advances in fields such as information technology, business analytics and additive manufacturing (Ivanov et al., 2018). Hence, IoT is expected to play a major role in enabling the digitalisation of the supply chain. In order to understand such role it is necessary to review relevant work in the area of IoT in the supply chain to identify gaps and opportunities.

Ashton (2009) coined the term IoT to refer to uniquely identifiable interoperable connected objects with RFID technology. In a supply chain context Ben-Daya et al. (2017) acknowledged that "IoT is a network of physical objects that are digitally connected to sense, monitor and interact within a company and between the company and its supply chain enabling agility, visibility, tracking and information sharing to facilitate timely planning, control and coordination of the supply chain processes". The definition provided by the authors emphasised the requirements for digital connectivity of the physical things in the supply chain; as well as facilitating data storage, analysis and sharing; intra and inter-organisational transactions and enabling the planning, control and coordination of supply chain processes. Figure 1 depicts a schematic representation of technologies that can generate large amounts of data for the supply chain such as wireless sensors, smart meters, radio links, RFID tags in trailers, electronic toll collection among others used in the context of IoT.

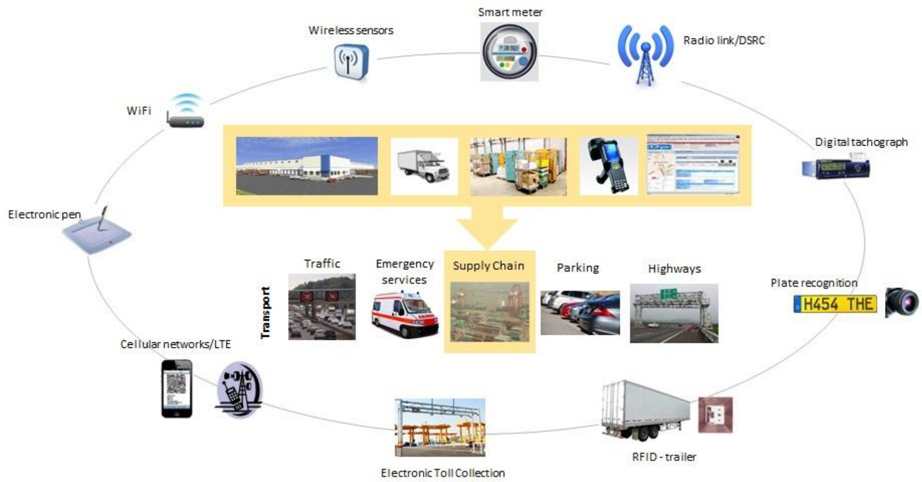

Figure 1. Various technologies that can be used for the supply chain in the context of IoT

IoT-enabled devices can feed into multiple applications including traffic, emergency services, parking, highways, etc. Since IoT is associated with a large number of wireless sensor devices, it generates a huge number of data (Chi et al., 2014). Arunachalam et al. (2017) recognised that the last decade has seen significant growth in the adoption of numerous ICT for Supply Chain Management (SCM) comprising from RFID, Enterprise Resource Planning (ERP) to IoT and as a result this has triggered huge data generation in the supply chain. In recent years logistics organisations have been at the frontline of adopting IT applications. The term 'logistics informationisation' coined by Zheng et al. (2012) refers to the use of modern information technology with lots of basic data needing entry and processing in logistics processes.

In recent years supply chain and logistics operations have been active adopting IoT solutions. For example container tracking usually relies on RFID tags which are attached to containers, boxes and pallets included in the shipment and then recorded at a number of points along the way (Harris et al., 2015). RFID tags are widely used to track and trace different types of cargoes. The RFID tag may be attached directly to the cargo or carried by the driver/operator of a haulage vehicle. Apart from RFID, IoT can be related with more technologies such as wireless sensor networks (WSN), barcodes, intelligent sensing, low energy wireless communications, cloud computing and others (Li et al., 2015). The delivery function is one of the main important tasks of logistics which involves planning and control of flow and storage of goods and services (Ben-Daya et al., 2017).

In the academic literature it is possible to find examples of researchers addressing the technical aspects of IoT. For example, the work found in Postcapes (2018) provided a list of IoT protocols organised according to the layer they occupy in existing architectural models. These include: Infrastructure (e.g. IPv4/IPv6); Identification (e.g. EPC, uCode, IPv6); Communications/Transport (e.g. WiFi, Bluetooth, LPWAN); Discovery (e.g. Physical Web, mDNS); Data Protocols (e.g. Websocket, Node); Device Management (e.g. TR-069, OMA-DM); Semantic (e.g. JSON-LD, Web Thing Model) and Multi-layer Frameworks (e.g. Alljoyn, IoTivity, Weave, Homekit). The work by Xu et al. (2014) recognised the importance of a sound architecture to support the decentralised and heterogeneous nature of IoT. The researchers indicated that the architectural design of IoT covers a wide range of items including architecture styles, networking and communication, smart objects, Web services and applications, business models and corresponding process, cooperative data processing, security and many more. Furthermore, they proposed a four-layer approach to achieve interoperability between heterogeneous devices. These comprise: *a)* a sensing layer where wireless smart systems such as sensors have the ability to sense and exchange data among different devices; *b)* a networking layer which makes possible to connect all things together and to exchange information between them; *c)* a service layer based on middleware technology making possible the integration of services and applications in IoT and also processes all service-oriented issues, including information exchange and storage, data management, search engines, and communication; and *d)* an interface layer which contains a number of specifications that enable displaying information to the user while interacting with the system. Using a similar approach, Bi et al. (2014) developed a three-layer model comprising of an IoT platform, IoT application, and IoT industry solutions for the purpose of analysing the requirements of manufacturing and how it can benefit from the adoption of IoT infrastructure.

The sensing layer described in the work by Xu et al. (2014) and Bi et al. (2014) is closely related to the theory of WSN. In WSN data are forwarded (possibly using multiple hops) to a sink (sometimes denoted as controller or monitor) that can use it locally or which can be connected to other networks (e.g. the Internet) through a gateway/base station (Buratti et al., 2009). WSN can be generally described as a network of nodes that cooperatively sense and may control the environment enabling interaction between persons or computers and the surrounding environment (Verdone, 2008). According to Verdone (2008) in WSN, the activity of sensing, processing, and communication under limited amount of energy, ignites a cross-layer design approach typically requiring the joint consideration of distributed signal/data processing, medium access control, and communication protocols. Certainly, the theory of WSN has the potential to be developed into a network that supports IoT in supply chain applications. Indeed, the use of WSN theory can help evaluate the possibility of increasing the number of sensors in a specific geographic area and then determine the resulting associated energy consumption.

The collection of large amounts of data generated by IoT-enabled sensors require the use of suitable analytics algorithms. Cheng et al. (2017) acknowledged that in order to analyse massive amounts of data generated from both IoT applications and existing ICT systems, data science and data analytics techniques should be employed. Kang et al. (2016) highlighted the challenges associated to the analysis of IoT-generated data, characterised by its continuous generation, large amount, and unstructured format. The authors emphasised that IoT-generated data, such as RFID and sensor data, are not only constantly generated in real time as the supply chain and manufacturing processes continue, but also provided in a variety of data formats. The authors concluded that there would be an unprecedented number of transactions and amounts of data generated if several billion tags and sensors were connected through the Internet. The generation of high volumes of data is a main characteristics of IoT devices, as the work of Zhong et al. (2015) confirmed RFID devices can generate a huge volume of data. Supply chain operations play a fundamental role in several industries, one of them is food which in recent times has been adopting IoT solutions. The next section reviews some representative works of the use of IoT in the food industry.

2.1 Applications of IoT in the food industry

In the food industry the term ‘food chain’ refers to the total supply process from agricultural production, harvest or slaughter, through primary production and/or manufacturing, to storage and distribution, to retail sale or use in catering and by consumers (Stringer and Hall, 2007). Here a significant number of innovations have been adopted resulting in the management of complex supply chains involving food production, processing, distribution and preparation and also as consequence of increasing customer awareness of food safety. The consolidation of the temperature and humidity-controlled food chain is perhaps one of the main developments that have affected the food chain.

IoT developments are having a major impact on the food industry and its associated supply chain. The use of IoT in the food supply chain shows a high degree of specialisation depending on the type of requirement being addressed. The work by Kuo and Chen (2010) highlighted that in temperature sensitive and perishable products (TSPPs) logistics, a special type of supply chain management was established, namely Cold Chain Management –CCM-. The authors highlighted that the physical logistics system of a cold chain is configured to minimise the cost of storage and transportation, and to meet the requirements of product quality. Traceability linked to information sharing using IoT is a major area of interest. The review by Bibi et al.

(2017) focused on the RFID component of IoT and how the agrifood sector has become one of its most promising areas of application. Their work identified traceability as the tracking of the food product in the supply chain, from production, to transportation, storage and delivery stages.

The survey carried out by Li et al. (2015) provided a detailed review of the impact of IoT on the food supply chain. The researchers highlighted that IoT technologies offer promising potentials to address the traceability, visibility, and controllability challenges as it can cover the food supply chain in the so-called farm-to-plate manner, from precise agriculture, to food production, processing, storage, distribution, and consuming. Furthermore, the authors commented on a typical IoT solution for food supply chain (the so-called Food-IoT) made of three parts: *a)* the field devices such as WSN nodes, RFID readers/tags, user interface terminals, etc.; *b)* the backbone system such as databases, servers, and many kinds of terminals connected by distributed computer networks, etc.; and *c)* the communication infrastructures such as WLAN, cellular, satellite, power line, Ethernet, etc. Working in the same area of research, Shih and Wang (2016) developed a cold chain system for a multi-channel Chinese food processing operation comprising a centralised kitchen and transportation to branch stores. The authors recognised that future opportunities will have to address fusing big data mining with IoT architectures.

IoT research in the food supply chain is active addressing some important challenges faced by the industry. On the importance of temperature in food safety and quality during storage and supply, the work by Lorite et al. (2017) developed a smart sensor integrated to a RFID tag to enable real-time monitoring of the food supply chain. Developments on traceability and information sharing include the work by Yan et al. (2016) who addressed the challenge of insufficient information sharing in agricultural supply chains. The authors developed a system that can be used to control safety and quality of agricultural products for the purpose of helping producers trace the flow of products. In a similar approach Chen (2017) developed an intelligent value stream-based food traceability cyber physical system for traceability and collaborative efficiency. Regarding emerging technologies in food, Verdouw et al. (2016) used a case about fish distribution to introduce the concept of virtualisation which is seen as a powerful approach to handle the complexity of the food supply chain. In the view of the authors virtualisation can be useful to decision-makers to monitor, control, plan and optimise business processes remotely and real-time via the Internet based on virtual objects.

Access to weather and climate data is highly valuable in food production. In the fisheries sector analytics can be used to identify the effects of changes in weather conditions in catch volumes of commercial species. The work by Puspasari et al. (2019) assessed the impact of extreme conditions on the sardine fishery of the Bali Strait. In their study the researchers noted that the sardine fishery in Bali is influenced by fishing effort and environmental conditions including seawater temperature and chlorophyll a (chl-a). The researchers collected data from two landing places and downloaded data for seawater temperature and chl-a from satellite readings. Using a regression model and profile analysis the researchers were able to estimate the impact of seawater temperature and chl-a concentration on sardine production and to measure how extreme periods have an impact on the catch composition in the Bali Strait.

The review of IoT in the food sector showed few examples that combine hardware with analytics components. The review showed a shortage of data analytics capabilities regarding IoT in food supply chains. Only the supply chain virtualisation concept introduced by Verdouw et al. (2016) included a data analytics component within an IoT architecture in the food supply chain. The implications of data analytics in the food supply chain can be significant, parting from the principle that data analytics using data collected through IoT networks help expedite timely decision-making (Xu et al., 2018). It is possible to appreciate a gap in the literature here where a shortage of data analytics capabilities may limit the possible benefits that can be obtained from IoT. Table 1 summarises the key areas identified in the review of examples comprising IoT in the food industry.

IoT application in the food supply chain	Strategic objective	Source
Cold chain management system	Minimise cost of storage and transportation	Kuo and Chen (2010)
Food-IoT	Traceability, visibility and controllability	Li et al., (2015)
RFID tracking in agrifood supply chains	Traceability linked to information sharing	Bibi et al. (2017)
Smart sensor integration for real time monitoring	Temperature control in food safety and quality	Lorite et al. (2017)
Information sharing system	Traceability of the flow of products in agricultural supply chains	Yan et al. (2016)
Value stream-based cyber physical system	Food traceability and collaborative efficiency	Chen (2017)
Virtualisation for decision making	Control, plan and optimise business processes in fish distribution	Verdouw et al. (2016)
IoT architecture in a cold chain system	Food processing and efficient transportation	Shih and Wang (2016)

Table 1. Applications of IoT in the food industry

The majority of the reviewed examples did not incorporate two or more complementary technologies within the sphere of IoT applied to the food supply chain. Among the various food supply chains that can be selected, fisheries offer significant opportunities. In recent years, the fisheries sector has been under pressure to improve its visibility and increase the traceability of its products. On the other hand fisheries have been traditionally perceived as a low-tech industry, basically a technological laggard when it comes to the adoption of new technologies. Nowadays the fisheries sector is experiencing an increased pressure from consumers demanding to trace the origin of the products they purchase. Overall, there is as a beginning of paradigm shift technologies comprising IoT and intelligent sensors which are transforming the fisheries sector.

The discussion regarding IoT solutions in the food industry and the noticeable opportunity to develop an approach that includes complementary technologies (as it would be the case of WSN theory along with elements of data analytics) has motivated the formulation of the following research question:

- How two complementary technologies comprising WSN theory and elements of data analytics can be integrated into an IoT approach for managing the supply chain in the fisheries sector?

The motivation for this work is supported by claims from some authors like Ben-Daya et al. (2017) in the sense that IoT systems can block large amounts of data, resulting in lost opportunities comprising predictive modelling and decision-making. They added that decision-making in an IoT context requires tools and models that consider this new environment, characterised by the abundance of big data generated from sensors and connected things. The use of WSN theory along with analytics capabilities can be part of a comprehensive set of IoT solutions that can support the fisheries supply chain.

3. A proposed conceptual approach for managing the digitalisation of food supply chains in a context of IoT – integrating wireless sensor network with data analytics

The literature review section identified the use of a multilayer approach when it comes to dealing with copious amounts of data generated by a vast number of heterogeneous devices operating in an IoT-enabled supply chain environment. The proposed conceptual approach used in this work is shown in figure 2 and it is related to the multilayer models from Xu et al. (2014), Bi et al. (2014) and Li et al. (2015). In our proposed approach it is possible to appreciate two major layers: the inner layer (IoT – sensor and network) and the outer layer (application).

In figure 2 these interdependent layers comprise important elements of analysis required in the management of the supply chain characterised by the use of IoT sensors/devices. In the sensor and network layer is where all the sensing activity takes place and also where sensors can be clustered to create a network enabling a more efficient energy consumption and transmission of sensors' readings. The use of Wireless Sensor Networks (WSN) theory meets the operation requirements of clusters of sensors given its purpose activity of sensing, processing, and communication under limited amounts of energy.

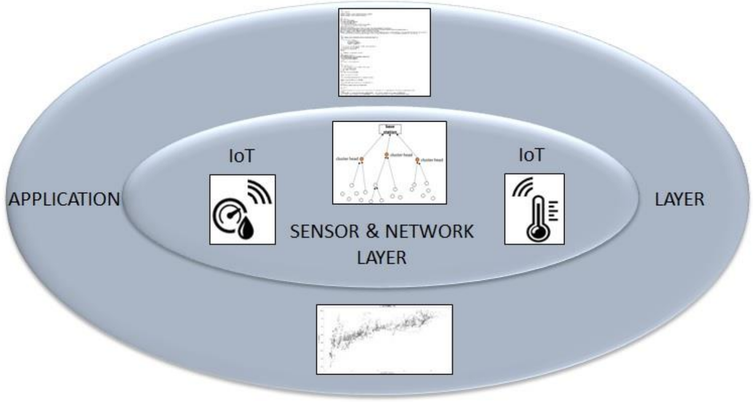

Figure 2. A two-layer conceptual approach for managing the digitalisation of fisheries supply chains

Potentially WSN theory can be used to simulate a network of sensors for IoT in a supply chain environment. The work by Buratti et al. (2009) recognised that in WSNs the nodes can be static or moving, they can be conscious of their position or not and they can be the same or not. Also Buratti et al. (2009) identified a possible scenario with multiple sinks in the network, where a sink represents a 'cluster head' and given a certain level of node density, a larger number of sinks will reduce the probability of isolated clusters of nodes that cannot deliver their data due to adverse signal propagation conditions.

The sensor and network layer is particularly important as wireless micro sensors are key to support ubiquitous access and transmission of data. According to the work by Kwon and Gerla (1999) an effective wireless sensor network protocol must consider system lifetime where nodes are designed to be extremely energy efficient. The focus of this work is on energy efficient/system lifetime, hence we selected the low-energy adaptive clustering hierarchy 'LEACH' algorithm which can be used to simulate WSN theory comprising a network of sensors for IoT. This algorithm is a protocol architecture for micro-sensor networks that according to Heinzelman et al. (2002) is characterised for having the following features: *a)* randomised, adaptive, self-configuring cluster formation; *b)* localised control for data transfers, *c)* low-energy media access control (MAC) and *d)* application specific data processing. Heinzelmann et al. (2002) explained the sink/cluster head node in the 'LEACH' algorithm obtains data from all the sensors that are members of the cluster, the data collected is used to perform signal processing functions (e.g. data aggregation), and then the data are transmitted to remote base stations with all non-cluster head nodes transmitting their data to the sink node. Figure 3 depicts the clustering hierarchy used in the 'LEACH' algorithm.

In the sensor and network layer, sensors collect readings from the detection of events taking place or changes in the environment. Through the use of access points, switches and routers that data are transmitted, stored and then used by applications run by the user and found in the application layer.

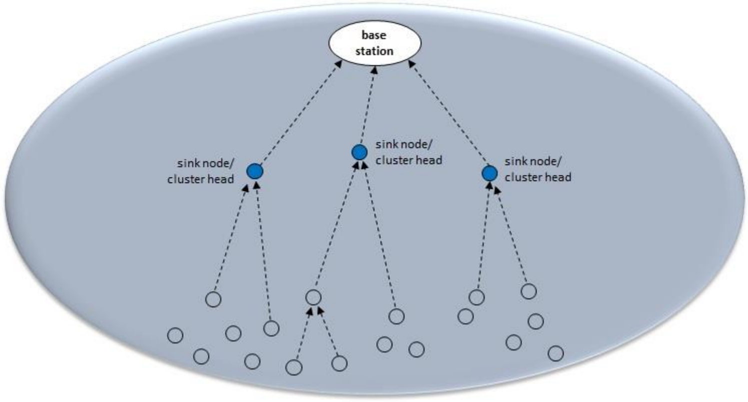

Figure 3. Clustering hierarchy used in the sensor and network layer

Data analytics in the context of IoT faces some specific challenges. This is mainly because IoT devices generate high-volumes of data, hence the need to use appropriate data analytics tools. The analytics component found in the application layer relies on the implementation of time series for the purpose of predictive analytics. As previously mentioned in the introduction section, predictive analytics involve the use of mathematical algorithms and programming to discover explanatory and predictive patterns within data (Wang et al., 2016). The development of data analytics found in the application layer is motivated by the fact that many studies have focused on conceptualising the impact of IoT with limited analytical models and empirical studies (Ben-Daya et al., 2017).

In the view of Sanders (2015) analytics applications that can deliver a competitive advantage can be seen all along the supply chain decision spectrum—from targeted location-based marketing to optimising supply chain inventories to enabling robust supplier risk assessment. Academics like Waller and Fawcett (2013) have discussed the implications of predictive analytics in emerging concepts such as ‘maker movement’ supply chains. Nonetheless, time series analysis accounts for the fact that data points taken over time may have an internal structure (such as autocorrelation, trend or seasonal variation) that should be accounted for (NIST/SEMATECH, 2013). Time series routines written in languages such as Python can be used to support the visualisation of large datasets comprising thousands of records as helpful means to identify trends, assist with monitoring tasks and support decision-making. In the proposed approach data are processed running a time series analytics routine written in Python to generate results in the form of scatter diagrams which are used to support decisions concerning the deployment of resources at the point of capture in the fisheries supply chain.

4. Methodology used

This work used data from an industry case involving the fisheries sector off the coast of the province of Newfoundland and Labrador in the Atlantic coast of Canada. The advantages of using an industry case is that it allows a holistic and contextualised analysis and it is appropriate for the initial phases of the exploratory nature of research work (Buganza et al. (2011). In general, this work is exploratory in nature and involves applied research. The purpose of formulating a research question is to provide the direction of enquiry and enable the connection between the research and its practical and theoretical contributions (Dubé and Paré, 2007).

This work is based on the fisheries sector, hence the proposed conceptual approach focuses on the point of capture which is the first stage of the supply chain. At the point of capture, the use of WSN theory based on the 'LEACH' algorithm allows modelling the energy consumption of the sensors reading the conditions in which fisheries capture fish/crustaceans. Using historical data from sensor readings, the next step is a time series analysis to identify trends by visualising the outputs generated by a routine written in Python. We use a large dataset with just over 10,000 records from the SmartAtlantic initiative. The dataset contains sensors readings coming from ocean buoys off the coast of Newfoundland in the Atlantic coast of Canada. The flow of actions comprising the analytics component of the proposed approach in the fisheries sector is illustrated in figure 4.

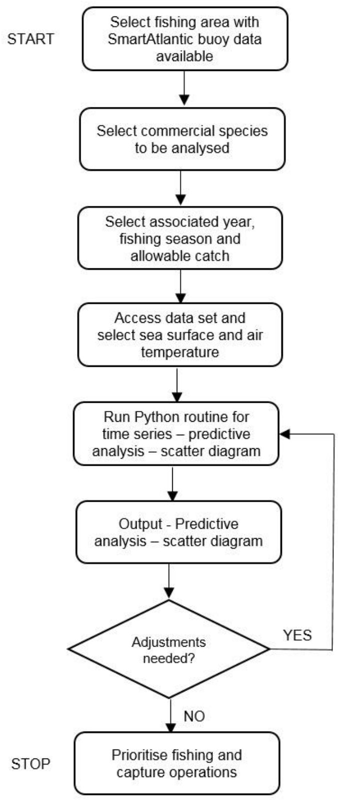

Figure 4. Diagram of the flow of actions of the analytics component – fisheries sector

In figure 4 the start of the process is represented by the selection of the specific fishing area with Smart Atlantic buoys data available, this step is followed by the selection of the specific commercial species of fish/crustaceans to be analysed. The next step is to select the associated year, fishing season and allowance catch associated to the selected species of fish/crustaceans. The next step involves access to the dataset with the sensor readings for the selected geographic area. A code routine written in Python provides the required predictive analysis – scatter diagram for the selected dataset. The output enables the visualisation of two variables (average sea temperature and air temperature) through a scatter diagram. Adjustments will be required in case of inconsistencies in the output. If no adjustments are needed, the output generated may help identify trends where ocean monitoring and meteorological conditions can contribute to superior fishing/catches volumes and also prioritise capture/fishing operations.

5. Using the conceptual approach for managing the fisheries supply chain (e.g. snowcrab): SmartAtlantic Alliance - A Network of Oceanic Observation Sensors in Atlantic Canada

In this section the proposed conceptual approach is applied to the specific case of the SmartAtlantic (2019) initiative which is a system of oceanic observation buoys championed by the Marine Institute of Memorial University of Newfoundland and the Institute for Ocean Research Enterprise in Halifax, Nova Scotia, Canada. In its origin, the SmartAtlantic initiative started as an aid for navigation to mariners in the Port of Placentia Bay, Newfoundland, the second largest port in Canada (by value of goods, mostly oil and oil products) (SmartAtlantic, 2019). In the beginning the initiative was called SmartBay, as it was implemented in different locations in Atlantic Canada but then it changed its name to SmartAtlantic. Currently, the initiative consists of eight oceanic observation buoys in eight different locations. These buoys are located in (SmartAtlantic, 2019): Exploits (Newfoundland); Bay of Island (Newfoundland); Conception Bay (Newfoundland); Halifax (Nova Scotia); Placentia Bay (Newfoundland); Port-aux-Basques (Newfoundland); Saint John (New Brunswick) and St. John’s (Newfoundland).

In Newfoundand and Labrador it is possible to find five fishery divisions as defined by the Northwest Atlantic Fisheries Organisation (NAFO, 2019): 2HJ, 3KL, 3PS, 4R and 3PS. However only a handful of areas have smart buoys which are part of the SmartAtlantic initiative. This work uses as a reference the conditions found in the Red Island shoal buoy in Placentia Bay. Figure 5 illustrates the location of the buoy to be used as a reference as this represents the point of capture and the first stage in the fisheries supply chain. Parameters at the point of capture can be stored and used as reference for supply chain monitoring purposes including storage handling, required tamper proof checks especially in exports, product history and also provenance tracking.

The fishing industry in the Canadian province of Newfoundland and Labrador (NL) has been the backbone of the provincial economy. It is also a very important component of the social tissue for Newfoundlanders and Labradorians. For more than 200 years of economic provincial history, the fishing industry in NL has been dedicated and focused mostly on the fishing, processing and commercialisation of groundfish. Lobster and various types of groundfish including cod, haddock, halibut, Greenland turbot, flatfish, pollock, and others are captured in the province.

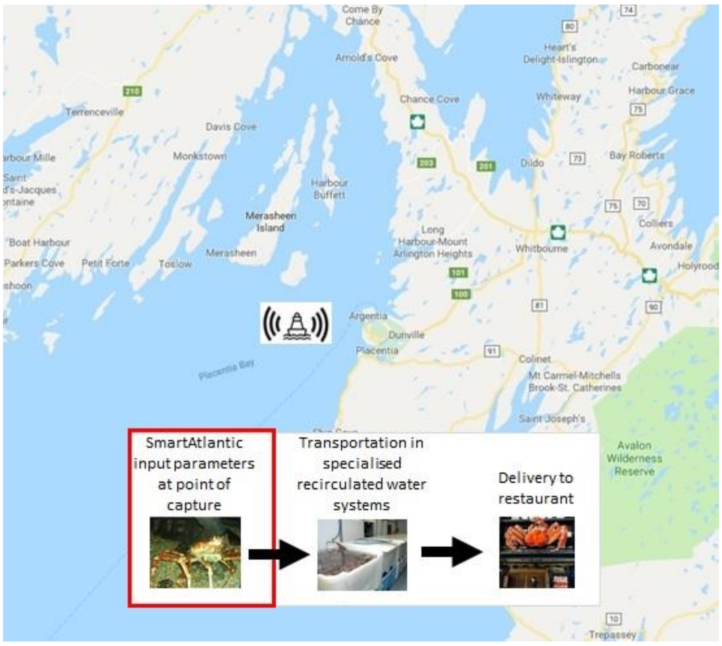

Figure 5. Red Island shoal buoy with highlighted point of capture in the fisheries supply chain

Snow crab, king crab and other perishable shellfish products are captured in the fishery area 3PS. Among crustaceans, snow crab commands a higher value. Seafoodnews (2019) reported that in early 2019 prices for Newfoundland, Gulf and Russian snow crab have been trading in the \$8.50 to \$8.60 per lb range. In Newfoundland and Labrador the snow crab fishing season opens in early April for the island portion of the region and early to mid-May for Labrador, and harvesters participate as environmental conditions in the different fishing areas permit (Fisheries and Oceans Canada, 2019).

5.1 Running WSN theory for ocean observation sensors

Using the Red Island shoal buoy in Placentia Bay as a reference, a Matlab implementation of the 'LEACH' algorithm was developed and tested. The buoys used in the SmartAtlantic project capture 15 different measurements that include: average speed wind (m/s), peak wind speed (m/s), wind direction from (°magnetic), air temperature (°C), barometric pressure (millibars), humidity (%), dew point (°C), average sea surface temp (°C), maximum wave height (m), significant wave height (m), peak wave period (sec), average wave direction from (°magnetic), average wave spread (degrees relative), average current direction toward (°magnetic) and average current speed (mm/s). In the case of crustaceans, temperature readings are particularly important because many of these animals can live only in very specific and narrow temperature ranges. The use of WSN theory give us the opportunity to evaluate the possibility of increasing the number of nodes in the geographic area surrounding the buoy and the resulting increase in the number of packets exchanged between sensors and the base station. An increase of nodes is directly related to the increase in the number of sensors.

The results shown in figure 6 considered an area of 1000 m X 1000 m, where reading sensors can be distributed to record readings involved in the point of capture of snow crab. The 'LEACH' algorithm does the function of placing nodes randomly within the boundaries of the defined area. The 'LEACH' model parameters include the initial energy supplied to each node (E0) equal to 0.5 J. For each one the energy required to transmit/received a message over the designated distance (Eelec) is equal to 50 nJ/bit. The energy used for data aggregation (EDA) is equal to 5 nJ/bit/signal. The bandwidth of the channel was set to 1 Mb/s and each data message was 500 bytes long (Heinzelman et al., 2002).

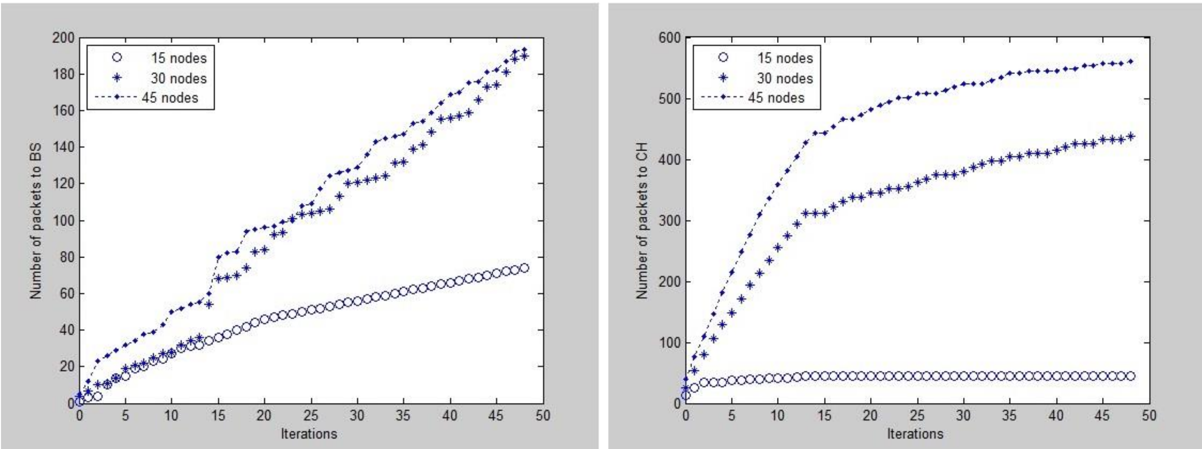

Figure 6. Results from simulations using WSN theory based on the 'LEACH' algorithm for ocean buoy sensors

The results show that when the number of nodes is low, in this case 15, the number of packets sent to the base station experienced a high growth rate as iterations increase. On the other hand, when the number of nodes present is higher, say 30 and 45, the increase in the number of packets to the base station experience a low growth rate which tend to stabilize as iterations increase. An increase in the number of nodes has the possibility to increase the accuracy of sensor readings for a specific geographic region.

The simulation included the number of packets sent between clusters as this has an effect on the performance of WSN. The values plotted in figure 6 show that when the nodes present in the network is low, say 15 for an area of 1000 m X 1000 m, the number of packets exchanged between clusters experience high growth levels. It was decided to model 48 iterations as 48 sensor readings take place during every full day the buoys operate. According to the values obtained for 48 iterations, the number of packets sent by 15 nodes to the base station reached 6, for 16 nodes the number of packets sent reached 18 for 40 nodes the number of packets sent to the base station reached 25. For 20 nodes the number of packets sent to the cluster head is equal to 6. For 16 nodes the number of packets sent is equal to 16 and for 40 nodes the number of packets reaches 52. For 8 nodes the initial energy supplied is equal to 10 J, for 16 nodes is 30 J and for 40 the amount is 50 J.

In the scenario presented here, the number of packets sent can be related to the metered readings of meteorological conditions recorded during the capture of crustaceans (e.g. snow crab) in that specific geographic area. Energy consumption is paramount hence, there has to be considerations in place about the maximum number of nodes that can be present in the network. There may be a temptation to increase de number/sensors for the sake of improved accuracy but doing so it will result in an increase in energy consumption. As the proposed application is at sea level there are no physical obstructions that may hinder its operation.

5.2 Running analytics for ocean buoy sensor data

After the completion of WSN theory analysis, data analytics was performed on a dataset of readings for the Red Island shoal buoy in Placentia Bay associated to the 3PS fishery division as defined by NAFO. The data chosen covers four years (2016-2019). The data is freely available at the SmartAtlantic project website (https://www.smartatlantic.ca/PlacentiaBay/). The data available can be analysed in a manner where it could be possible to detect trends related to the conditions associated to the capture of crustaceans (e.g. snow crab) like sensor readings for average sea surface temperature (°C) and air temperature (°C). Performing a predictive analysis gives the opportunity to identify possible correlations for those two readings. A routine for time series – scatter diagram was implemented in Python to analyse the data running in an online compiler available at: anaconda3/Jupyter notebook. This tool enables writing and executing Python, within a "notebook" in a web browser. The output from the Python routine supports visualisation which represents helpful means when it comes to decision-making in the management of the supply chain. The output of the analysis can be of great value when linked to other data closely linked to fishing activities such as season fishing dates and allowable catch tonnage among others.

The snow crab fishing season generally starts in April/May and it ends in late June for the 3Ps area. Division 10A north of Placentia Bay north of 46°30'N. Snow crab lives in narrow temperature ranges between -1 °C and 3 °C. Table 2 shows the season dates, duration of each season, total usable sensor readings available and allowable catch for snow crab.

Year	Season dates	Duration	Total usable readings	Allowable catch (tonnes)
2016	4 April – 15 June	73 days	3392	1,120
2017	15 April – 15 June	62 days	1321	560
2018	9 April – 15 June	68 days	1575	672
2019	9 April – 30 June	83 days	3721	1,008

Table 2. Year, dates of fishing season, duration and allowable catch of snow crab for 3Ps area division 10A.

For the four years analysed, there were a total of 409 sensor readings missing (99 for the year 2016; 153 or the year 2017; 55 for the year 2018 and 102 for the year 2019), the total number of usable sensor readings was 10,009. With the data selected it was possible to perform predictive analytics of the readings for average sea surface temperature (°C) and air temperature (°C) which represent the conditions associated to the catch of snow crab in the 3Ps area, division 10A. The time series analysis in the form of scatter diagrams for the readings comprising the years 2016, 2017, 2018 and 2019 are shown in figures 7, 8, 9 and 10 respectively.

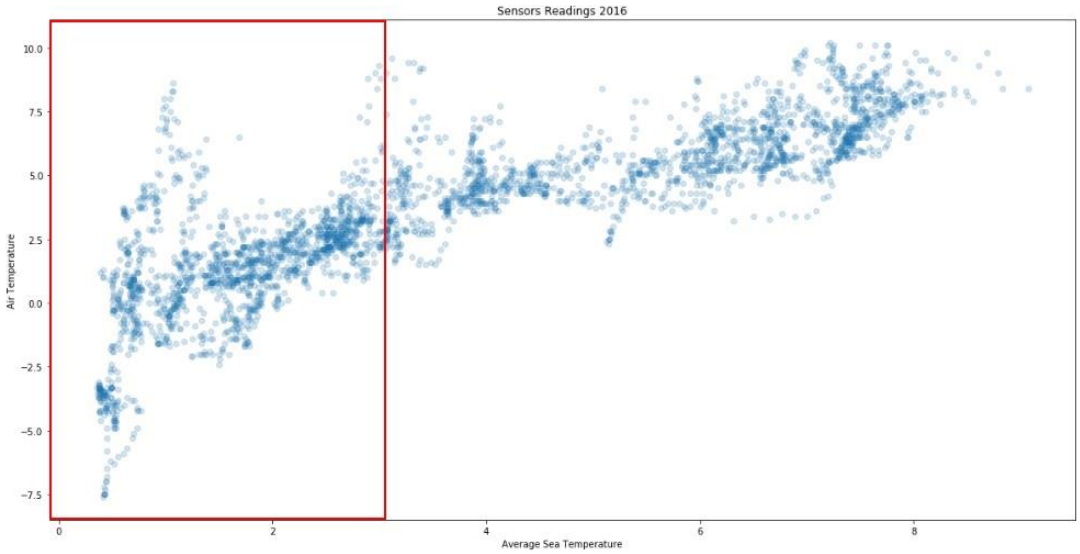

Figure 7. Time series/scatter diagram for year 2016.

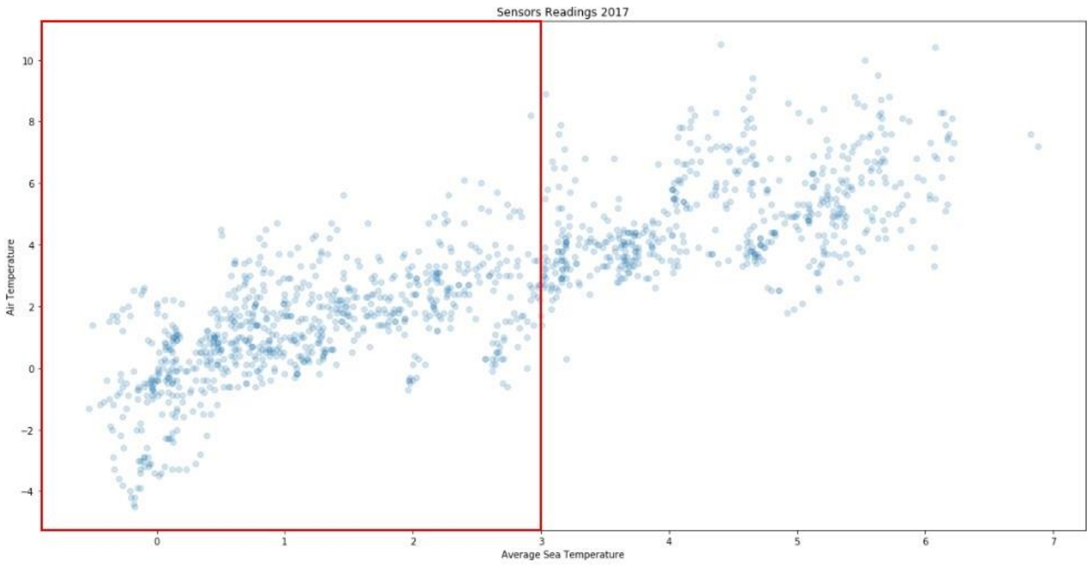

Figure 8. Time series/scatter diagram for year 2017.

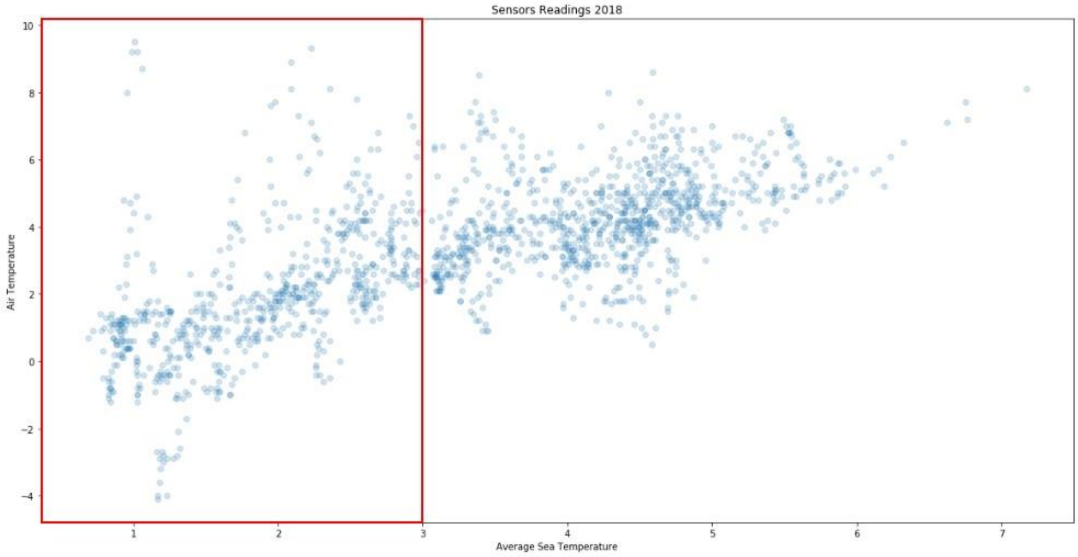

Figure 9. Time series/scatter diagram for year 2018.

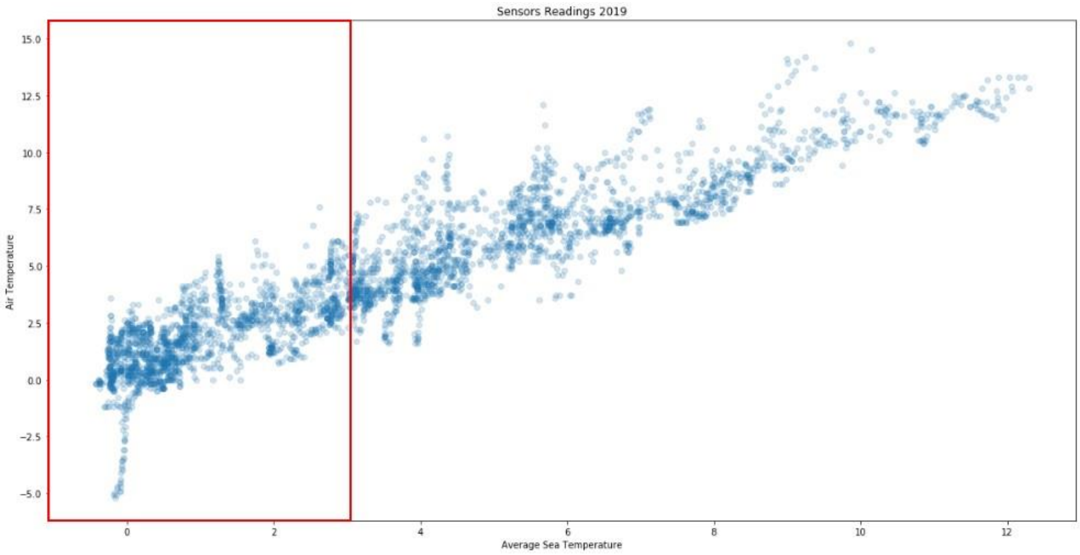

Figure 10. Time series/scatter diagram for year 2019.

The use of scatter diagrams in time series analysis represents a powerful tool that can help to identify important patterns regarding the conditions in which snow crab is captured. Given the facts that snow crab is a species of crustacean that lives in narrow temperature ranges between -1°C and 3 °C, the best chance for higher yields in the 3Ps area, division 10A is actually during the start of the fishing season, in the month April and early May. Figures 7, 8, 9 and 10, include a window that indicates that narrow temperature range. The scatter diagrams show the records for air temperature are the coldest when average sea temperatures are between the ranges of ---1°C and 3 °C.

The snow crab is an animal that will migrate to zones with colder waters as soon as average sea temperatures start to raise. In the year 2016, from 5th of May, average sea temperatures consistently started to record temperatures of 3°C and over, as a consequence, the chances of high catches of snow crab in that region started to decrease. In the year 2017 continuous temperatures of 3°C and over were reported from May 15^{th} and in the year 2018 from 8^{th} May. In the year 2019 temperatures of 3°C and over were continuously recorded from 14^{th} May onwards.

It is worth highlighting the estimated economic value associated with the capture of snow crab given the year-on-year fluctuations in both price and the allowable catch for each of the four years comprising this case. In the year 2016 the value of 5-8 oz Newfoundland snow crab had a value of roughly $7/lb (Sackton, 2019). In 2017 the value of snow crab reached about $8/lb and in 2018, the value went up to $8.20/lb and in 2019 that value reached $8.50/lb (Sackton, 2019) (1 tonne = 2,204.62 lb). Table 3 shows the estimated commercial value for the four years comprising this case.

Year	**Price per lb**	**Allowable catch (tonnes)**	**Estimated commercial value**
2016	$7/lb	1,120	$17,284,220.00
2017	$8/lb	560	$9,876,697.60
2018	$8.20/lb	672	$12,148,338.00
2019	$8.50/lb	1,008	$18,889,184.00

Table 3. Year, price per lb, allowable catch and estimated commercial value in the 3Ps area, division 10A

Table 3 shows the significant impact that annual price per lb and allowable catch can have on the commercial value of snow crab for the 3Ps area, division 10A. For example, in the year 2017 the estimated commercial value was almost half of the estimated commercial value for the year 2016. Eventually estimated commercial value recovered in the following two years. Limits to allowances depend on several factors that may include quotas, sustainable fishing practices, demand, etc. In the past demand for snow crab was fuelled by the Japanese market but that marked has been experiencing a decline in recent years (Sackton, 2019).

6. Implications

Digitalisation is a process that is changing the face of supply chains in several sectors and fisheries is not the exception. It is well acknowledged that the fisheries and the fishing industry in general has been prone to lack of quality (in product and processes) and product fraud by malicious product mislabeling and falsification of records (Coronado et al., 2019). The process of digitalisation gives the fisheries sector the unique opportunity of better traceability which represents a method to provide safer food supplies and to connect producers and consumers (Regattieri et al., 2017).

The proposed conceptual approach presented in this paper can be seen as an integrative scheme that incorporates two of the most important elements required in the management of the supply chain in the fisheries sector: sensor network management and analysis of the data generated by the same sensors. This approach is important for fisheries and the fishing industry as the point where animals are captured represent the very beginning of the supply chain of the lucrative seafood business. The use of sensor network theory may allow better sensor management without experiencing substantial penalisation associated to power consumption. Large datasets generated by sensor readings will have to be examined using times series analytics/scatter diagram. The results of data analytics may give place to optimised fishing operations focusing at the beginning of the fishing season when the average sea temperature is well within the narrow temperature range that animals like snow crab thrive in. Another consequence is that daily tonnage catches can reach their maximum at the beginning of the fishing season.

Other sectors where the proposed framework can be applicable may include crops, vegetable/fruit, poultry, livestock and mining, among others as these share similar requirements with the fisheries sector. Moving upstream in the supply chain closer to the point of origin and access sensor records involving production conditions may give the possibility of optimised operations and the capacity of dealing with events such as recalls which require access to product history and provenance tracking.

7. Conclusions and future research

The process of digitalisation affecting the supply chain is the result of the combination of various technologies in the context of IoT. In the literature it is possible to find several examples of frameworks and models that have addressed the impact of technology on the food supply chain. Hence, a noticeable opportunity was identified to combine sensor management with a data analytics element. We believe this work makes a contribution to the growing body of knowledge on supply chain digitalisation in the fisheries sector by presenting a conceptual approach that integrates sensor management using Wireless Sensor Network (WSN) theory and the analysis of high volumes of sensor-generated data through a Python-based time-series scatter diagram routine. The use of WSN theory may assist organisations run a growing network of sensors at highly efficient energy levels. Furthermore, the use of time-series scatter analysis may help organisations identify important trends and patterns that may lead to improved scheduling of fishing/capture operations.

An important particularity of this work is that it focuses at the point of origin/capture in the supply chain. Although the proposed approach presented in this paper has been applied to the specific characteristics of the fisheries sector, the fact is that many other sectors require tight levels of control from the point of origin of their respective supply chains. In the fisheries sector, the point of capture requires recording the conditions in which animals are captured. This action represents a key step because these recordings will become part of the supply chain ledger/records that have to be available until the product reaches the hands of the end customer. Furthermore, in the fisheries and seafood sector these recordings will be required for supporting supply chain control and monitoring of activities including purpose of transportation, handling storage, tamper proof checks, product history and provenance tracking (Coronado et al., 2019).

The proposed conceptual approach can be seen as an aide for mapping the supply chain at the point of origin/point of capture in the presence of IoT devices. Future work may consider expanding data analytics to include algorithms that enlarge the scope of the data analysis such as forecasting validation among others. It seems digitalisation will continue to have a growing impact on every aspect of the supply chain including sustainability and security in the supply chain, not to mention better control and decision-making. We believe future research work needs to investigate in more detail the associated economic impact of IoT-enabled devices in the supply chain of food and perishable goods.

Finally, future research involving the study of the process of digitalisation in the supply chains of seafood/perishable goods sector will have to consider emerging technologies such as blockchain technology. Food and perishable goods represent one of the most data-oriented logistics-type of businesses and also prone to disruptions. The use of blockchain technology may result in higher reliability of information compared to the use of conventional ways of exchanging information.

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