Inf Syst Front (2015) 17:289–319
DOI 10.1007/s10796-012-9374-9

Value-centric design of the internet-of-things solution for food supply chain: Value creation, sensor portfolio and information fusion

Zhibo Pang · Qiang Chen · Weili Han · Lirong Zheng

Published online: 29 August 2012

Abstract The revolution of Internet-of-Things (IoT) is reshaping the modern food supply chains with promising business prospects. To be successful in practice, the IoT solutions should create "income-centric" values beyond the conventional "traceability-centric" values. To accomplish what we promised to users, sensor portfolios and information fusion must correspond to the new requirements introduced by this income-centric value creation. In this paper, we propose a value-centric business-technology joint design framework. Based on it the income-centric added-values including shelf life prediction, sales premium, precision agriculture, and reduction of assurance cost are identified and assessed. Then corresponding sensor portfolios are developed and implemented. Three-tier information fusion architecture is proposed as well as examples about acceleration data processing, self-learning shelf life prediction and real-time supply chain re-planning. The feasibilities of the proposed design framework and solution have been confirmed by the field trials and an implemented prototype system.

Keywords Internet-of-things (IoT) · Food supply chain · Value-centric design · Sensor portfolio · Information fusion · Industrial information integration engineering (IIIE)

Z. Pang (✉) · Q. Chen · L. Zheng
iPack Vinn Excellence Center,
School of Information and Communication Technology,
Royal Institute of Technology (KTH),
Isafjordsgatan 39,
164 40 Kista-Stockholm, Sweden
e-mail: zhibo@kth.se

Q. Chen
e-mail: qiangch@kth.se

L. Zheng
e-mail: lirong@kth.se

Z. Pang
Corporate Research, ABB AB,
Forskargränd 7,
721 78 Västerås, Sweden

W. Han
Software School, Fudan University,
No. 825, Zhangheng Road,
Shanghai, Peoples' Republic of China
e-mail: wlhan@fudan.edu.cn

L. Zheng
School of Information Science and Technology, Fudan University,
No. 220, Handan Road,
Shanghai, Peoples' Republic of China

1 Introduction

1.1 Technology explorations

The Internet-of-Things (IoT) is a vision of connectivity for anything, at anytime and anywhere, which may have an impact on our daily life dramatically as what the Internet has had in the past two decades (ITU 2005). European Commission Information Society (2008) has defined IoT as "*Things having identities and virtual personalities operating in smart spaces using intelligent interfaces to connect and communicate within social, environmental, and user contexts*" or "*Interconnected objects having an active role in what might be called the Future Internet*". The term of the IoT is often associated with such terms as "*ambient intelligence*", "*ubiquitous network*", "*ubiquitous computing*", "*pervasive computing*", and "*cyber-physical systems*". Key enabling ICT (Information and Communications Technology) technologies include radio frequency identification (RFID), wireless sensor network (WSN), machine-to-machine communication (M2M), human machine interaction (HMI), middleware, web service, information systems, etc. With multiple visions from different viewpoints, the IoT has become the common paradigm of modern ICT area (Atzori et al. 2010). It offers immense potential to consumers, companies and public sectors by enabling innovative applications and services in nearly all sectors of economy. In the strategic research roadmap (European Commission Information Society 2009), the application of IoT in food supply chains (FSCs) is one of the promising killer applications. Covering from precision agriculture, to food production, processing, storage, distribution, and consuming, so-called *farm-to-plate*, IoT solutions provide promising potentials to address the traceability, visibility and controllability challenges. Safer, more efficient, and sustainable FSCs are expectable in the near future.

The state of the art of some IoT-related technologies for FSC-related applications has been reviewed in recent years. Ruiz-Garcia et al. (2009), Ruiz-Garcia and Lunadei (2011) have reviewed the RFID and WSN technologies for farming environmental monitoring, fire detection, farm machinery, pest control, animal tracking, viticulture, precision irrigation, greenhouse, food traceability, precision livestock, supply chain management, cold chain monitoring; and Lee et al. (2010) have reviewed the sensing technologies for precision specialty crop production. After a review of the above literatures, we found that IoT applications in FSCs are still in an early stage with low maturity; and although pilot projects have covered many aspects of the FSCs, the solutions are still separated and lack of comprehensive considerations. Furthermore, when we assessed the recent solutions (Huang et al. 2006; Jones 2006; Kuck 2007; Hsu et al. 2008; Abad et al. 2009, Martínez-Sala et al. 2009, Carullo et al. 2009; Ruiz-Garcia et al. 2010, Sallabi et al. 2011, Qi et al. 2011, Rong et al. 2011; Hulstijn et al. 2011; Lao et al. 2012), above findings were confirmed. A detailed comparison is given in Table 6 by mapping them to the exploration space proposed in section 1.3. For the above analysis, the existing solutions can resolve only a part of the problems either in business or in technology. Additionally, although some of them look relatively comprehensive, (e.g. Martínez-Sala et al. 2009 and Jones 2006), the benefits for users are highly limited by the RFID technology that they use.

So, as the main aim of our work, it is of significance to overcome the above drawbacks. In particular, we intend to propose a business-technology joint design framework; and then base on that, to design a better solution to resolve the problems in a more comprehensive way. Effectiveness of the design framework is proven by the feasibility of this real solution.

1.2 Business applications

Besides the technology explorations, business applications have also been actively carried out during the recent years. These mainly include behavior observation, benefit identification, business process representation, business logic modeling, price and cost modeling, performance evaluation, etc. According to our investigation, we found the existing studies are either inadequate in technology alternatives (mainly RFID rather than the IoT) or too general in applications (general supply chains rather than specific FSCs). Specific explorations on IoT-for-FSC are far from comprehensive and practical.

In the last decades, the e-commerce and information technology have demonstrated great impact on supply chain management (SCM) (Li 2007). To improve global supply chain integrity, the effective use of information technology and IT infrastructure has become one of the central topics in relevant areas (Li and Warfield 2011). The technologies will allow real-time collaborative SCM, supply chain integration, and supply chain quality management in the face of complex and fast-changing market conditions (Xu 2011b). By observing the users' behavior, Angeles (2010) has proven the positive relationship between RFID application attributes (equivalent to adoption willingness to some extent) and the level of both IT infrastructure integration and supply chain integration. Going a step further, strategic business benefits of RFID have been identified (Tajima 2007; Sarac et al. 2010, Ugazio and Pigni 2010, Wamba and Chatfield 2010). But these studies address the supply chain problems in general, without specific considerations of FSCs. Being more specific for FSCs, benefits (Choe et al. 2009), process models (Victoria de-la-Fuente and Ros 2010) and pricing models (Zhang and Li 2012) have been studied. But technology alternatives considered in these studies are only the traditional RFID which is only a small subset of key IoT technologies. Moreover, the significant setbacks have happened in the adoption of RFID technology, and debates and criticism still commonly exist today (McWilliams 2006). There is no consensus about "*what is the correct path for RFID*", but at least we all agree that "*its adoption hasn't followed the predicted path when it was firstly promoted by Wal-Mart*" (Visich et al. 2011). Therefore, more business research on IoT-for-FSC, beyond the RFID-for-SC, are essential to lead the industry to a correct direction.

So the second aim of this work is to enhance the business applications by extending the technology alternatives from RFID to the IoT, and concentrating the application scope from general supply chains to FSCs.

1.3 The whole pictures

Today's typical FSC is a distributed system with large geographical and temporal scale, complex operation processes, and diverse technical requirements. It is impossible to map it into the virtual world without classification and formalization. In our previous work (Pang et al. 2012), we have abstracted the real FSCs into 5 scenarios: *Produce*, *Store*, *Transport*, *Sell* and *Consume*. A scenario is the abstraction of a class of similar deployment environments. It is not always equal to one transaction step in real business process; instead it may correspond to multiple transaction steps or a part of a single transaction step. Any real FSC can be composed by all or a part of the 5 scenarios under certain orders and topology.

As shown in Fig. 1, a typical IoT solution for a FSC comprises: a series of field devices (WSN nodes, RFID readers/tags, user interface terminals, etc.), a backbone system (databases, servers, and many kinds of terminals connected by distributed computer networks, etc.); and a series of heterogeneous wired and wireless communication infrastructures (WiFi, cellular, satellite, power line, Ethernet, etc). Due to its ubiquitous connectivity, all physical entities of field devices and backbone equipments can be distributed throughout the entire FSC. Through powerful but economy sensing functionalities, all environmental and event information can be gathered on a 24/7 basis. The vast amount of raw data is extracted and fused into high level and directly usable information for decision support systems (DSS).

As mentioned above, the IoT-for-FSC is "mashup" of business and technology explorations. So taxonomy is necessary to have an overall picture of the exploration space. Here we use a three-level classification framework proposed by Sheng et al. (2010), and refer to the taxonomy proposed by López et al. (2011). By adding a "business level" to the three-levels, stacking the four-levels over the five-scenario model of FSCs, we get a whole picture of the exploration space of IoT-for-FSC. An example is shown in Fig. 2. It will be used to compare the existing solutions and position our work.

1.4 The business-technology joint design framework

"*Changing business strategies is the name of the game*" and "*firms are embracing the underlying technologies of the Internet of Things to optimize their internal processes, expand their traditional markets and diversify into new businesses*"(ITU 2005). From the enterprise point-of-view, the IoT is the fundamental infrastructure of future enterprise information systems (EIS) (Sinderen and Almeida 2011; Xu 2011a). The emerging topic of industrial information integration engineering (IIIE) have introduced a number of advanced techniques to establish the future EIS, but great challenges exist especially in terms of dimensionality and complexity (Xu 2011a). To cross the gap between industrial business practices and technology development, a business-technology joint design is essential to bring successful IoT solutions into the market. A good solution must resolve both technical and business challenges simultaneously. The technology explorations and business applications should be closely combined instead of separated. Unfortunately, we have rarely seen this in open literatures.

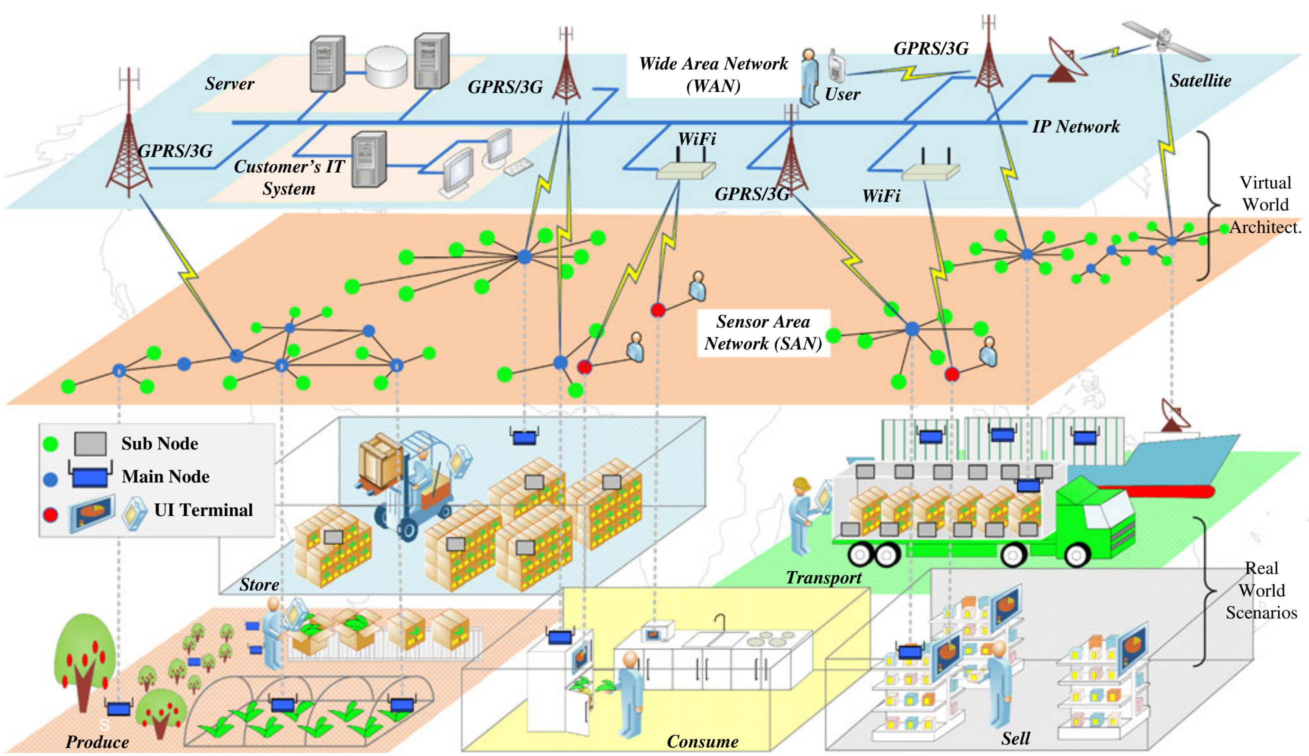


Fig. 1 A whole picture of food supply chains in the era of Internet-of-Things

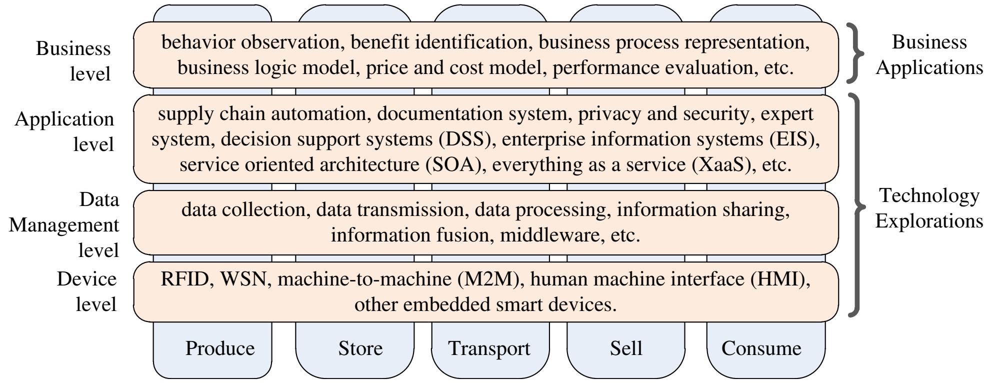


Fig. 2 A whole picture of the exploration space of IoT-for-FSC

Motivated by this issue, we propose a more comprehensive joint design framework as shown in Fig. 3. There are two interfaces to link the business application and technology exploration: information requirements and information delivery corresponds to knowledge exchange between the both sides. The information requirements are derived by value creation in the business side, and then generate the sensor portfolios and information fusion algorithm in the technology side. The information delivery is derived from the information fusion in the technology side, and then should be evaluated by value assessment in the business side. The key of this design framework is the knowledge exchange by describing "*what information is essential from business point-of-view*" and "*how should the information be provided by technology*". This knowledge exchange is also a kind of knowledge-fusion among multiple subjects ranging from ICT, to agriculture, food engineering, management engineering, public administration, etc. Only when the information requirements and information delivery match very well, the business benefits can be delivered to users with sufficient satisfaction. Otherwise, the design result is unqualified.

Additionally, this framework is value-centric instead of technology-centric as users pay only for values instead of technologies. So "what information the technology *should* provide" is prior to "what information the technology *can* provide". From this point-of-view, the traditional RFID is far from satisfactory because it provides too little "information" (identification, time, etc.). A real IoT solution must provide much richer "information" by richer sensor portfolios, advanced sensor data processing and high level information fusion. This point is consistent with the analysis of the setbacks of RFID technology (McWilliams 2006; Visich et al. 2011).

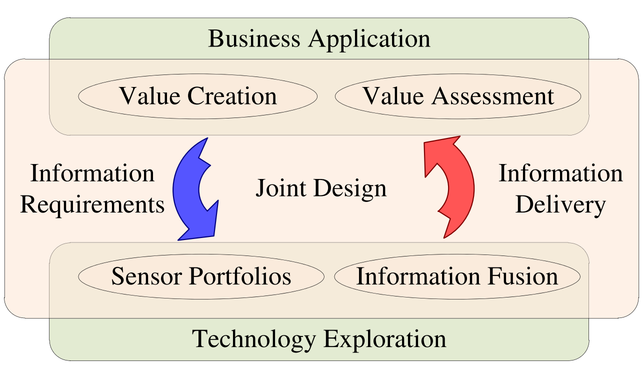


Fig. 3 The business-technology joint design framework

1.5 Overview of this paper

In the rest of the paper, technical details of the proposed value-centric design framework will be presented by introducing a real solution.

We start from value creation by analyzing the traceability-centric values in traditional RFID-for-FSC and identify more income-centric values by our literature study and market research. Then the values created above are assessed by a quantitative stakeholder analysis throughout the entire value chain including consumers, enterprises and public sectors. More attractive "income-centric" added-values such as shelf life prediction, sales premium, precision agriculture, and reduction of assurance cost are highlighted beyond the conventional traceability. After that, comprehensive sensor portfolios are developed in a systematic way, by exploring causes of food spoilage, comparing available sensing technologies and products, and evaluating the energy and traffic costs. Three-tier information fusion architecture is proposed by mapping all data processing and information delivery functionalities into a global scale "cooperative food cloud". Acceleration data processing, shelf life prediction and real time supply chain re-planning are introduced as examples of on-site, in-system, and in-cloud information fusion respectively. Finally, the implemented prototype system and results of field trials are presented. The feasibilities of the proposed design framework and solution have been confirmed. Limitations and future works are discussed too.

Based on the exploration space and design framework introduced above, we position and compare our work with other recent ones in Table 6. We can see that, our work covers all the exploration levels and scenarios due to the whole picture and comprehensive considerations. By providing richer sensor portfolios and information fusion functionalities, we can accomplish what we promised to users. By applying the proposed value-centric design framework, the IoT solution providers can step closer to a business success.

The rest of the paper is organized as follows: the value creation and assessment is presented in section 2; sensor selections and the derived sensor portfolios are given in section 3; in section 4, we describe concrete information fusion architecture and detailed examples; the implemented prototype and field test results are introduced in section 5; limitations and future works are discussed in section 6; and conclusions are drawn in section 7.

2 Value creation and assessment: Beyond the traceability

2.1 Traceability-centric values of traditional RFID

In traditional RFID-for-FSC applications, traceability is at the center of the added values offered to users. According to EU regulation on food chain safety, traceability refers to the ability to trace and follow a food, feed, food producing animal or ingredients, through all stages of production and distribution (EU 2002). In particular, it includes the ability to find the product location, to recall the characteristics or origin, and to track a product batch and its history through the whole food production chain from harvest through transport, storage, processing, distribution and sales (Hsu et al. 2008).

The primary drivers of food traceability system are from public sectors, such as food supervision organizations and public health agencies (Boddie and Kun 2008, Lao and Wang 2008). Their primary aim is to effectively prevent or restrict the spread of food safety accident which is a big issue to public safety. Another aim is to resolve the "paradox" in food industry: on one hand, the critical requirements of quality need the suppliers to react quickly to the changes of demand; on the other hand, the nature of food production prohibits food suppliers from adjusting their plan frequently. Due to the lack of effective feedback mechanisms, the food availability oscillates between periods of overproduction and shortage (European Commission Information Society 2008). Additionally, the feedback of adjustable reorder, daily usage and machine breakdown can effectively confirm the order fill rate and reduce supply disruption rate (Liu and Kumar 2011).

In conventional RFID-based food traceability systems, RFID are mainly used to record all kinds of IDs (products', processes', and operators') over time. The same functionalities are already provided by the maturated barcode technology, although slower but much cheaper. The main improvement of RFID is faster reading speed and longer reading distance, which can hopefully reduce labor cost and process time. But this benefit is inadequate to drive the entire food chains to adopt. The main reason is the "traceability" cannot directly and quickly contribute to enterprises' financial performance. On the contrary, the big initial investment causes short term financial pressure. This point has been proven by business studies in third party logistics industries. Although such traceability system can enable many process innovations, "*the suppliers were reluctant to adopt the RFID because their initial investment cost, required by the third party logistics firm, has produced the minimum level benefits for themselves, which, in turn, has a cascading effect on the minimum level business benefits realized by the TPL firm*" (Wamba and Chatfield 2010). A recent survey has confirmed this too (Visich et al. 2011). Therefore, new value creation beyond traceability is essential to bring IoT-for-FSC into successful business.

2.2 Income-centric values creation

Tajima (2007) has summarized 15 potential benefits of RFID for general supply chains: 1) reduced shrinkage, 2) reduced material handling, 3) increased data accuracy, 4) faster exception management, 5) improved information sharing, 6) production tracking, 7) quality control, 8) supply & production continuity, 9) material handling, 10) space utilization, 11) asset management, 12) reduce stock outs, 13) customer service, 14) after sales service, and 15) lower inventory. These benefits are relevant to different roles in the supply chain: 1~5 relevant to the whole value chain, 6~8 to manufactures/suppliers, 9~11 to distributors/logistic providers, and 12~15 to retailers. This study has tried to extend the values from traceability to direct financial contributions. However, these nice expectations are limited by the simple functionalities of RFID devices. The benefits that a real RFID solution can deliver to users are often far from the promise. Li (2011) has proposed a generic framework to assess the relational benefits of logistics service providers in supply chain. The result has indicated that, three relational benefits (value-added benefits, collaborative benefits, and economic benefits) are expectable by the stakeholders; these benefits will exert influence on relational outcomes (such as sales volume, market position and smooth supply chain process); and good relational outcome will serve as the basis for the development of trust and long-term relationship. This study has expanded the thinking of value creation and assessment to broader enterprise viewpoints by emphasizing the business values. By considering the specific requirements and constraints in FSCs, as well as newest development of other key IoT technologies (sensing, information fusion, etc.), more attractive values have been proposed in some pilot business research. Some of them are selected and described below.

1) *Shelf Life Prediction*: Various technologies have been proposed to predict the shelf life of the food, e.g. time temperature integrators (TTI, an enzymatic label with changing color depending on time and temperature) (Tsironi et al. 2011) and high performance wireless sensor devices with on-site shelf life estimation (Jedermann et al. 2011). The shelf life prediction can change the conventional First-In-First-Out inventory management principle. "*The higher microbial load products with shorter remaining shelf life will be promoted for quicker selling and consumption in the closer market, whereas the lower microbial load and longer remaining shelf life can be directed for longer further distribution and be sold and consumed at satisfactory quality*" (Tsironi et al. 2008). For example, when a batch of banana is transported from Brazil to Sweden, the journey lasts typically 6 weeks by ships, trucks and trains. To harvest the bananas before maturity and then ripen them during transportation (under carefully controlled conditions) is a common method to deal with the long journey. It often happens that the conditions exceed the expected ranges. This accident shortens the bananas' shelf life significantly so that many of them spoil before reaching the retailer. If this accident could be detected timely, the destination may be modified to a shorter place, e.g. France, according to shelf life prediction. By this logistics re-planning, the sales price can be optimized.
2) *Sales Premium*. A survey conducted in Korea has proven that, consumers are willing to purchase greater quantities and pay higher prices for foods managed with long term tracking and monitoring systems (Choe et al. 2009). The essential reason is that, the system can effectively reduce "fear of seller opportunism" and information asymmetry so as to increase product diagnosticity and trust. This can be achieved by providing consumers concrete records of handling and environmental conditions. From enterprise' point-of-view, this sales premium (price premium in addition to purchase intention) contributes directly to their finance performance. By this means, the FSC monitoring and quality diagnostics can form a positive interaction between suppliers and consumers. Therefore this benefit could be a powerful driver of the adoption.
3) *Precision Food Production*: The application of IoT in food production can increase efficiency, productivity and profitability of producers. Meanwhile, it can minimize unintended impacts on wildlife and environment. The real time information from the fields will provide a solid base for farmers to adjust strategies timely, instead of making decisions based in hypothetical average condition (Ruiz-Garcia et al. 2009). For example, it has been used to monitor crops' growing process and control environment conditions in greenhouses (Yoo et al. 2007; Lea-Cox et al. 2007), to monitor productive cycle of high-quality wine for accurate planning of interventions in the field and preservation of the stored product (Anastasi et al. 2009), to measure and forecast the soil moisture and control the irrigation system to maximize productivity while saving water (Kim et al. 2008), etc. The increased productivity as well as product quality will of course increase the income of suppliers.
4) *Insurance Cost Reduction:* The insurance sectors play an important role in the value chain of IoT. Numbers of key benefits are brought to insurance companies including reduction in claim related expenses, reduction in overall risk and "moral hazard" with little required effort from customer, improved customer loyalty through pro-activity and "problem solver" positioning, improved brand awareness through product differentiation. It also brings benefits to insurance customers including payment reductions, real-time monitoring of "hidden" areas, increasing sense of security, faster response to critical events minimizing damages of valuable items, unobtrusive and hidden system (Strauss et al. 2009). Enabled by IoT solutions, the insurance company "could request information from clients in order to gain a greater understanding of supply chain conditions at the time that loss of product occurred due to spoilage" and customers would benefit from the visibility, respond to temperature fluctuations, and better insurance plans/offering from the insurance company (Claire 2011). An example in real business is the Hartford Financial Services Group, a well-known insurance company that is providing insurance services to the food industry globally. They encourage their clients to apply wireless semi-passive temperature sensors by insurance premium discount. According to a case study in Taiwan, the insurance cost occupies as much as 9.94 %~14.3 % in the total start-up cost of a grocery store during the first 4 years (Hong et al. 2011). The reduction of insurance cost will significantly increase the profit margin of such stores. Therefore, insurance companies have great influence on the adoption of IoT technologies in FSC.

Here we introduce the above four values as an example of the new value-creation principle. They are actually a part of potential "income-centric" values that IoT solutions can offer. In a certain application, developers and users could create more than above. But no matter what new values are created, they all follow a common principle: income-centric instead of traceability-centric. The income-centric values can directly contribute to enterprise's financial performance in terms of income or profit. In contrast, traditional traceability-centric values often indirectly contribute to financial performance. For example, applying high-technologies like IoT could increase the image of brand which can, hopefully, increase the sales gradually. But this positive effect is non-deterministic and invisible in short term. Therefore, the income-centric IoT solutions could expect shorter payback period (P.P.) of investment than traceability-centric ones. The P.P. is the primary criterion for users to decide whether to adopt the new technology or not. Additionally, the development of IoT needs a new ecosystem. The income-centric values are the foundation of such ecosystems.

As a showcase, we identify the above four income-centric values (*shelf-life prediction, sales premium, precision agriculture, and insurance cost reduction*) and *traceability* as the result of value creation. These five values will be assessed in next subsection. And they will serve as inputs of sensor portfolios and information fusion which will be introduced consequently.

2.3 Quantitative value assessment by stakeholder analysis

In modern FSCs, a large number of stakeholders are involved ranging from individual consumers, to enterprises and public sectors. As previously mentioned, from different stakeholder's point-of-view, the main concerns and expectation are usually different. Correspondingly, different values should be created and promoted. In another word, "one size cannot fit everyone". So the value creations should be basically stakeholder-related. José et al. (2007) and Goff-Pronost and Sicotte (2010) have applied stakeholder-analysis methods in opportunity-challenge assessment in logistics and telemedicine industries. In their studies, the stakeholders' *influences, interests, and satisfactions* are quantized by a scoring matrix. Referring to these scoring tools, we have proposed a novel quantitative value assessment method as a part of the business-technology joint design framework.

1) Step 1: identify stakeholders. We divide all parties in the entire FSC into seven groups according to their roles in the value chain, so-called stakeholders, including *producer, logistics provider, wholesaler, retailer, insurance company, consumer* and *public sectors*.
2) Step 2: identify the values to be evaluated. As mentioned before, we will assess the five added-values provided by our solution.
3) Step 3: score every added-value by four parameters: influence_factor (IFL), interest_factor (ITR), devotion_factor (DVT), and satisfaction_factor (STF). The four parameters are defined below and benchmarked in Table 1. This step should be performed by means of market research, e.g. questionnaire survey or field interview, during which the subjective evaluation of the 4 parameters should be quantified.
   - *influence_factor*: expresses a stakeholder's ability to promote or inhibit the adoption of a IoT solution using this added-value as the primary selling point. The higher score means higher influence, no matter promote or inhibit.
   - *interest_factor*: expresses a stakeholder's willingness to achieve the benefits provided by this added-value. The higher score means higher interest to achieve.
   - *devotion_factor*: expresses how many resources (tangible or intangible including money, man-hour, or risk-taking) the stakeholder would like to devote to achieve such benefits. It should be distinguished from the *interest_factor.* Under business context, people always intend to achieve some benefits by paying as less as possible. They will not invest on a new technology unless they really believe they will be paid back. For instance, a stockholder may actively participate the free trials, but finally don't decide to sign the check for volume deployment. In this case, a high score to *interest_factor* and a low score to *devotion_factor* will be assigned.
   - *satisfaction_factor*: expresses a stakeholder's satisfaction with what they have actually achieved comparing to what the solution has promised. Higher score means the solution has higher ability to deliver this added-value to users. The *satisfaction_factor* is determined by the functionality and performance of a deployed system. This determines that the value assessment can only be completed after deployment and field test. In this section we present the preliminary result of the system that will be introduced in the following sections of this paper.
4) Step 4: fill in the results of step 3 into the scoreboard shown in Table 2, and calculate the *attractiveness_factor* (ATR) according to (1), where i is the index of stakeholders, N is the total number of stakeholders, α is a weight factor corresponding to different strategies, and *FullScore* is the highest possible score of each item. It is normalized to the range of (0, 100]. The *attractiveness_factor* expresses a weighted summary of a particular added-value regarded by all stakeholders. Higher *attractiveness_factor* implies higher attractiveness to the entire FSC, and hopefully higher possibility to market-success. By adjusting α, we get different assessment strategies. For example, the interest-first strategy (α=0.8) is more optimistic and emphasizes the power of user's interests; the devotion-first strategy (α=0.2) is

Table 1 Score benchmark of the factors in proposed added-value assessment framework

Score	IFL	ITR	DVT	STF
0	No impact at all	No interest at all	Devote nothing	Reject and claim for compensation
1	Very indirect influence	Like to follow up progresses	Can have a free try	Cannot accept
2	Indirect influence	Some interests, but it's ok without it	Can have a try with small cost	Some complains
3	Secondary participator	Can use it if commanded	Want to have with acceptable cost	Constructive suggestions
4	Main participator	Seeking solutions actively	Want to have regardless of cost	No good, no bad
5	Coordinator and commander	Eager to get it	Actively promote regardless of cost	Satisfied

more realistic and emphasizes the difficulties; and the balanced strategy (α=0.5) is the moderate one.

$$ATR = \frac{100}{FullScore^3} * \sum_{i=1}^{N} \left\{ STF_i^* IFL_i^* [\alpha * ITR_i + (1-\alpha)] * DVT_i \right\},$$
$$i \in [1, N], \alpha \in [0, 1] \quad (1)$$

The preliminary result of our showcase is shown in Table 2. In this showcase, the score data is synthesized based two sources: one is a questionnaire-based market research carried out in our previous work (Zhang 2010); another is a literatures based market research. The literatures include Tajima 2007; Tsironi et al. 2011; Jedermann et al. 2011; Tsironi et al. 2008; Choe et al. 2009; Ruiz-Garcia et al. 2009; Yoo et al. 2007; Lea-Cox et al. 2007; Anastasi et al. 2009; Kim et al. 2008; Strauss et al. 2009; Claire 2011, and Hong et al. 2011. From Table 2 we have noticed some interesting phenomenon. Without any doubt, to fulfill the consumers' concern about food quality and safety is the target of the whole industry. But the consumers' influence to the FSC is indirect and relatively weak. The public sectors have stronger influence by means of regulations, but sometime lower than other stakeholders too. The enterprises (producer, logistics provider, wholesaler, retailer, and insurance company) have more interests in the income-centric added-values than traceability. The more stakeholders that the benefit can reach, the more attractive it can be, especially when we look at the value of shelf life prediction, sales premium and insurance cost reduction. We also noticed that, the added-values are inter-dependent to some extent. For instance, high quality "*shelf life prediction*" could increase the attractiveness of another added-value "*insurance cost reduction*". To do value assessment for every individual added-value is to do a comparison and find out which one is most attractive to which stakeholder. This can strategically tell system designers how to highlight the solution, not only in development activities but also in marketing activities.

Finally, it is necessary to mention that, due to the limited scope of market research, the quality of the raw data in Table 2 needs to be improved in future study. For example, the data in the row of "insurance company" and the column of "precision agriculture" are only from literature review since we have no direct partner or contact. And as we haven't deployed the system in volume, the users' feedback

Table 2 Added-value assessment scoreboard: each 4-number-set means [IFL, ITR, DVT, STF]

Stakeholders	Added-values																			
	Traceability				Shelf life prediction				Sales premium				Precision agriculture				Insurance cost reduction			
Producer	5	3	1	2	4	3	2	2	3	5	5	3	5	5	5	3	2	4	3	3
Logistics P.	4	4	a2	3	5	4	3	4	4	5	5	4	3	5	4	4	5	5	5	5
Wholesaler	4	5	3	4	5	5	5	4	5	5	5	4	2	4	4	4	5	5	5	5
Retailer	4	5	3	4	5	5	5	4	5	5	5	5	2	4	3	4	3	5	5	5
Insurance C.	3	5	3	4	4	3	4	4	4	2	4	5	2	1	1	4	5	5	5	5
Consumer	1	5	3	4	3	5	5	4	2	4	4	4	2	4	4	4	1	1	1	5
Public S.	3	5	3	5	2	3	3	5	2	3	3	5	3	3	3	5	1	3	3	5
ATR (α=0.8)	41.03				50.24				52.57				32				56.32			
ATR (α=0.5)	35.2				49.83				53.94				31.31				56.11			
ATR (α=0.2)	29.37				49.42				55.31				30.63				55.91			

is not neutral enough. And distinguishing ability of scores is not enough either.

3 Sensor portfolios

3.1 Design procedure

In an IoT-for-FSC application, sensing functionalities determine the solution capacity and user satisfaction. Systematic considerations in sensor portfolios are important. In our business-technology joint design framework, the sensor portfolios are derived based on the result of value creation. The detailed procedure is shown in Fig. 4.

The first step is sensor targeting. In this step, we study in depth what information is required to deliver the highlighted values to users. For example, to deliver the basic value of traceability, the ID information of products and operators over time is required. To provide enough information for insurance companies to identify the place and responsibility of damage, localization information is necessary. While other three values need more complicated sensor information because we must identify what are the reasons for food product spoilage first. Finally we should get a gross sensing target list. “Gross” means this list is a complete set without considering market availability and technical maturity. Then in the second step, particular sensor products for every sensing target in the gross list will be selected based on availability analysis. To achieve sufficient user satisfaction, we must make sure the sensor products we choose are accurate enough as well as matured enough. At the same time, they also need to be reliable and long term available. The availability analysis is done by investigating and comparing multiple alternatives of each sensing target. Price and other technical information are also collected for the next step. In the third step, the costs of candidates are compared by cost assessment. The cost here includes not only the purchase price but also the power consumption, traffic cost, and maintenance cost. Deployment densities and sampling intervals, as well as other practical considerations, are decided by tradeoffs between resolution and cost.

After that, the final sensor portfolios are clearly specified including sensing targets, expected performances, costs, deployment densities, sampling intervals, etc. It is necessary to note that feedbacks among the above steps are necessary. At the same time, this procedure should be updated over time once new sensing technologies and products are brought out. Technical details of the sensor portfolios are presented in next subsections.

3.2 Sensing targeting

Besides ID and localization, to provide the values of shelf life prediction, sales premium, and reduction of insurance cost, many other sensing targets are identified by investigating reasons for food product spoilage throughout the FSC. The list must contain all necessary environmental conditions that can affect food quality and shelf life.

As shown in Fig. 5, main causes of food product spoilage are investigated by means of literature review. They are classified into four types: microbiological infestation, biochemical changes, mechanical damages, and physical changes. Then, relevant sensing targets are identified to monitor, evaluate and reduce these causes. The first class of sensing targets is environmental conditions that can speed up/down the spoilage processes. For example temperature, humidity, and gas concentrations (carbon-dioxide, oxygen and ethylene) can significantly affect the biological and biochemical kinetics. The vibration, shock and tilt are direct causes of mechanical damages. Another class of sensing targets is indicators of the extent of spoilage processes. For example, the concentration of hydrogen sulfide (H_2S) in sealed package can be measured as the indicator of chilled sea food’s spoilage (Man and Jones 2000). For another example, the ethylene is produced by the ripening process of fruits, and then the ethylene can accelerate the ripening processes in return. So the ethylene concentration can be used as indicator of fruit’s age. Additionally, different causes are interrelated because one cause may speed up the effects of other causes. For example, the mechanical damages can considerably speed up a series of microbiological infestations and biochemical changes (Martinez-Romero et al. 2004).

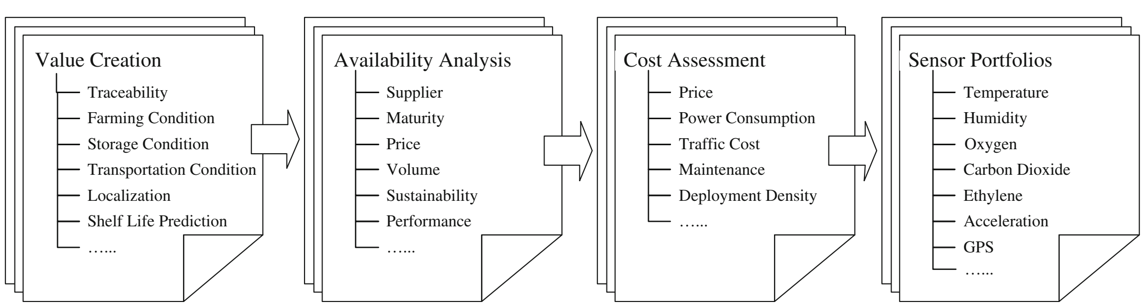


Fig. 4 Procedure to derive sensor portfolios

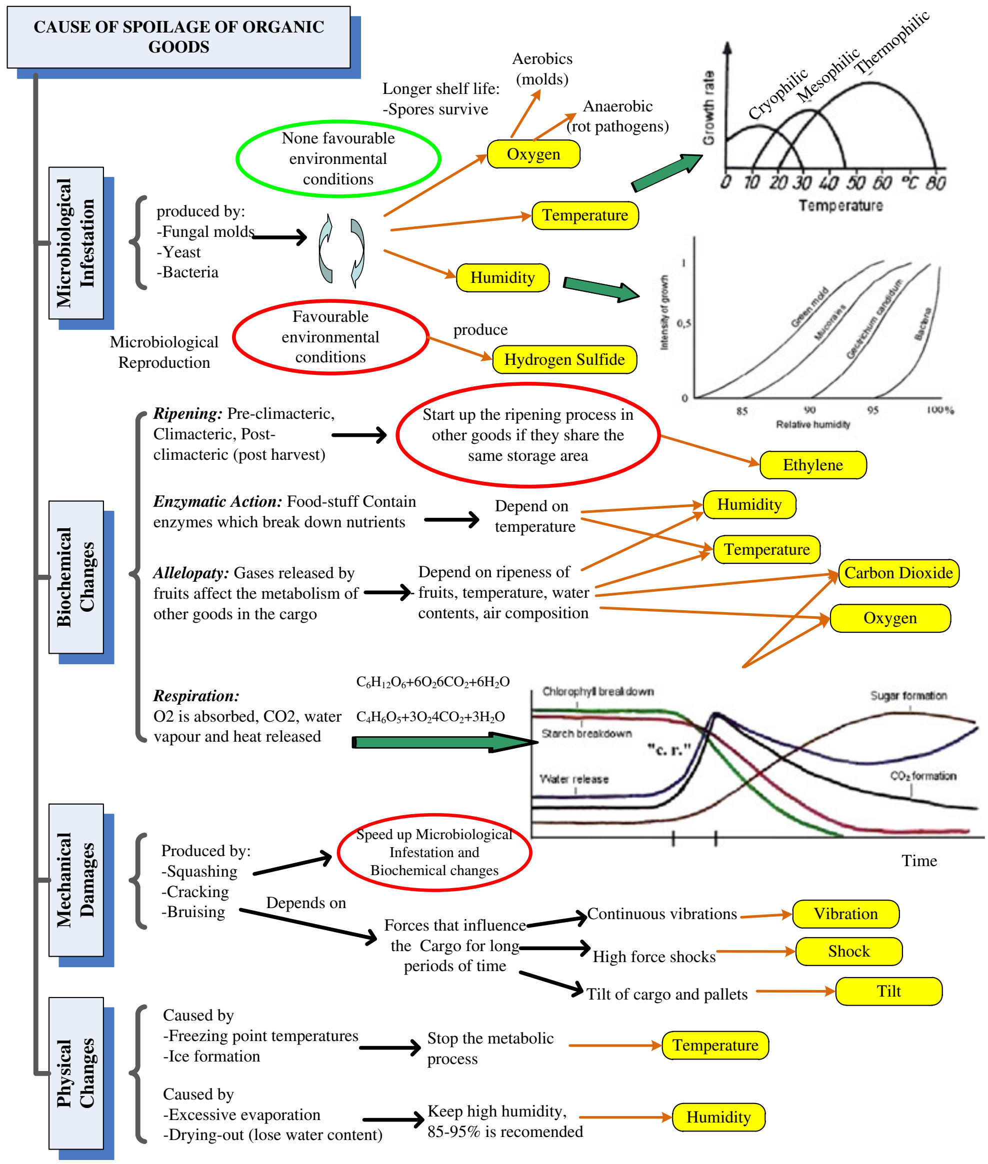


Fig. 5 Causes of food spoilage and sensing targets throughout FSCs (a summary based on German Insurance Association 2002–2011, Jedermann et al. 2011; Fellows 2000; Crisosto et al. 2008; Martinez-Romero et al. 2004, Man and Jones 2000)

For precession agriculture applications, soil moisture and ambient light are measured and analyzed to control automatic irrigation systems and/or greenhouse control systems (Ruiz-Garcia et al. 2009). And temperature, humidity, ethylene concentration, carbon dioxide concentration, and oxygen concentration are also necessary to optimize crop growth. Thus finally 12 sensing targets are identified in Table 3.

3.3 Availability analysis

For each sensing targets, the available technology alternatives, approximate price, maturity, and accuracy are compared in Table 3. Based on this analysis, we select the Global Positioning System (GPS) combing with wireless cellular for localization, integrated semiconductor transducer for temperature, integrated micro electro-mechanical systems (MEMS) transducer for humidity, infra red spectrum absorption detector for carbon dioxide, electrochemical sensor for oxygen, catalytic combustion sensor for ethylene, resistance measurement for soil moisture, integrated MEMS accelerometer for shock, vibration and tilt, and photo diode for ambient light. The list of alternatives is derived in Table 4. Further cost assessment will be done.

3.4 Sensor cost assessment

3.4.1 Energy cost

Limited power sources are primary technical constraints in the wireless sensor system design. So the power consumption of sensors is an important selection

Table 3 The sensing targets, possible sensor mechanisms and availability analysis

No.	Target	Possible mechanisms	Price	Maturity	Accuracy
1	Location	-GPS (Global Positioning System)	<$20	high	medium
		-Wireless cellular (GSM/3 G)	<$20	high	low
		-Short range wireless (WiFi, RFID or WSN)	<$20	medium	low
		-Ultra wide band (UWB)	<$500	low	high
2	Temperature	-On-chip temperature sensitive transistor	<$1	high	low
		-Integrated semiconductor transducer	<$1	high	medium
		-Temperature sensitive resistor	<$1	high	low
		-Thermal couple	<$50	high	high
		-Resistive Temperature Device (RTD)	<$500	medium	high
3	Humidity	-Humidity sensitive capacitor	<$1	low	low
		-Humidity sensitive resistor	<$1	low	low
		-Integrated MEMS humidity transducer	<$10	high	high
4	CO2	-Infra red spectrum absorption detector	<$200	high	high
5	Oxygen	-Electrochemical (oxidation-reduction)	<$100	high	high
6	Ethylene	-Catalytic combustion of combustible gases	<$50	high	high
7	H2S	-Electrochemical (oxidation-reduction)	<$100	high	high
8	Soil Moisture	-Resistance measurement	<$50	high	medium
		-Capacitance (dielectric constant)	<$100	high	high
		-Time domain reflectometer (TDR)	<$500	medium	high
9	Vibration	-Mechanical vibration switch	<$50	medium	high
		-Micro ball switch and counter	<$1	high	low
		-Integrated MEMS accelerometer	<$10	high	medium
10	Shock	-Mechanical vibration switch	<$50	medium	high
		-Micro ball switch and counter	<$1	high	low
		-Integrated MEMS accelerometer	<$10	high	medium
11	Tilt	-Earth magnetic and gravity sensor	<$100	medium	high
		-Integrated MEMS accelerometer	<$10	high	medium
12	Light	-Ambient light sensing photo diode	<$1	high	medium

Table 4 Cost assessment of sensors

No.	Target	Part number	Supplier	B_s Byte	I_{wu} mA	τ_{wu} s	I_{ms} mA	τ_{ms} ms	I_{pp} mA	τ_{pp} ms	E_s mJ
1	Location+	SiRF III GPS	CSR plc	28	0.72	25	45	5600	0.72	0.50	891
2	Temperature	SHT15	Sensirion AG	2	0.55	1.0	5.2	320	0.55	0.50	4.39
3	Humidity	SHT15	Sensirion AG	2	0.55	1.0	5.2	320	0.55	0.50	7.31
4	CO_2	IRceLCO2	City Tech.	4	28.5	35	33	1.50	28.5	0.50	3292
5	Oxygen	MicrocelO2	City Tech.	4	0.01	15	4.7	0.10	0.01	0.50	0.497
6	Ethylene	MicropeL75C	City Tech.	4	62	5.0	67	0.10	62	0.50	1023
7	H_2S	4 H CiTiceL	City Tech.	4	0.01	30	4.7	0.10	0.01	0.50	0.992
8	Soil Moisture	200SS-V	Irrometer Co.	2	1.5	0.50	6.1	0.10	1.5	0.50	2.48
9	Vibration*	MMA7361	Freescale Semi.	12	0.40	0.6	5.0	2.5	0.40	0.50	0.834
10	Shock*	MMA7361	Freescale Semi.	16	0.40	0.6	5.0	23	0.40	0.50	1.17
11	Tilt*	MMA7361	Freescale Semi.	6	0.40	0.6	5.0	1.5	0.40	0.50	0.817
12	Light	APDS-9003	Avago Tech.	2	2.5	0.01	7.1	0.10	2.5	1.0	0.091

+: The τ_{ms} is the warm-start time of GPS, which highly depends on the quality of signals from satellites. The results here are averaged by 100 tests in our Lab-room in Stockholm by placing the antenna on windowsill in heavy cloudy weather. This means relatively poor GPS signal quality

*: The tilt, vibration, and shock are simultaneously measured by a single accelerometer device combined with specific data processing algorithms (see section 4.2 for details). The results here are measured when statistic periods are 100 s

criterion. Energy cost is defined as the total energy consumption by the sensor device, external circuits, and micro controller operations to generate one valid "measurement". The "measurement" refers to one valid sample of the sensing target which is not always equal to a sample from analog-to-digital converter (ADC). For example, we use the accelerometer to measure vibrations. The accelerometer is continuously sampled at 20 Hz. Every 10 min, one sample of vibration is calculated by statistics of the accelerations during the 100 s. So the energy cost of vibration sensor should be energy consumed in the 100 s instead of 50 ms.

To calculate and compare, we use a state machine model of energy cost as shown in Fig. 6. The sensor working in one period is divided into three states: Warm Up state, Measure state, and Post-Process state. Within each state, we assume the power consumption is equal. We do not count the power consumption in sleeping mode or power-off mode in this step. First reason is the leakage current in standby mode is often much lower than working states. Second, the standby energy consumption depends on the sampling interval which may be different among sensors. Thus the standby energy consumptions are not directly comparable in our model. Of course, the standby energy consumption is not illegible, but we consider it in other models instead of sensor cost assessment.

The minimum energy consumption per sampling (E_s) is calculated by (2), where V_{wu}, V_{ms}, V_{pp}, I_{wu}, I_{ms}, I_{pp}, τ_{wu}, τ_{ms}, and τ_{pp} are the supply voltage, current and minimum duration of corresponding status.

$$E_s = V_{wu}{*}I_{wu}{*}\tau_{wu} + V_{ms}{*}I_{ms}{*}\tau_{ms} + V_{pp}{*}I_{pp}{*}\tau_{pp} \tag{2}$$

3.4.2 Traffic cost

In wireless sensor systems, the communication throughput is strictly limited by radio spectrum bandwidth, transceiver data rate, and communication protocol. The power consumption and design complexity increase much faster than the throughput. A slight increment in traffic load generated by one sensor may cause significant increment in the total cost of system. So the traffic cost of sensor must be taken into account.

The sensor traffic cost is expressed by the byte count per measurement (B_s). Similar to the meaning used in the energy cost model, the "measurement" refers to one valid sample of the sensing target instead of a sample from ADC. Also take the sample of vibration sensor, the raw data from ADC is 16 bits*3-axis=6 bytes per sample; but the statistic result of vibration is expressed by 12 bytes per measurement. Thus the traffic cost of vibration sensor should be 12 bytes per measurement instead of 6 bytes per measurement.

3.4.3 Cost assessment

We have investigated a batch of sensor devices and some of them are listed in Table 4. Key parameters for the energy cost model are measured in circuit. The micro-controller used in the test is MSP430F1611 from Texas Instrument Inc. running at 8 MHz. The supply voltages V_{wu},V_{ms}, and V_{pp}, are all 3.3 V.

The derived costs are plotted and compared in Fig. 7. We can see the sensors are basically divided into two classes. One class is so-called heavyweight sensors which are more expensive, power consuming and traffic intensive. Another class is so-called lightweight sensors which are of lower cost, lower power consumption and lighter traffic load. As a tradeoff between performance and cost, the heavyweight sensors should be deployed in lower density and the lightweight sensors in higher density. The lightweight sensors can have shorter sampling intervals than heavyweight sensors.

In our system, there are two types of wireless sensor nodes: Main Node (MN) and Sub Node (SN). MNs are more powerful than SNs in terms of power sources, communication capacity, and computing capacity, and of course have higher cost. Deployment density of MN is much lower than SN. A typical configuration is to use 16 SNs and 1 MN to form a Sensor Area Network (SAN). This configuration is firstly determined by the communication architecture and deployment constrains. Secondly, it also determined by the above cost assessment results. The heavyweight sensors (including carbon dioxide, oxygen, ethylene, GPS, soil moisture, hydrogen sulfide sensors) are designed in Main Nodes (MNs), and the lightweight sensors (including temperature, humidity, acceleration, and ambient light sensors) are designed in both MNs and Sub Nodes (SNs). The traffic costs and energy cost in Table 4 and Fig. 7 are calculated with this density (1 SAN includes 1 MN and

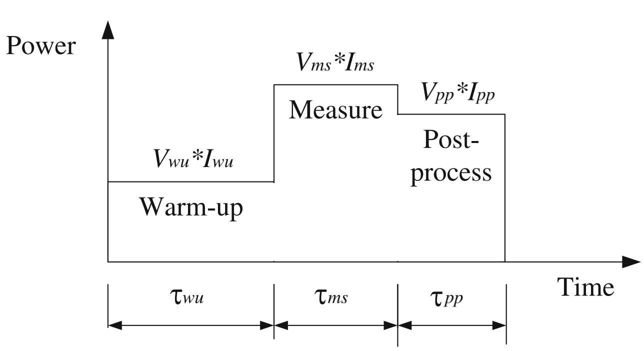


Fig. 6 Simplified sensor energy cost model

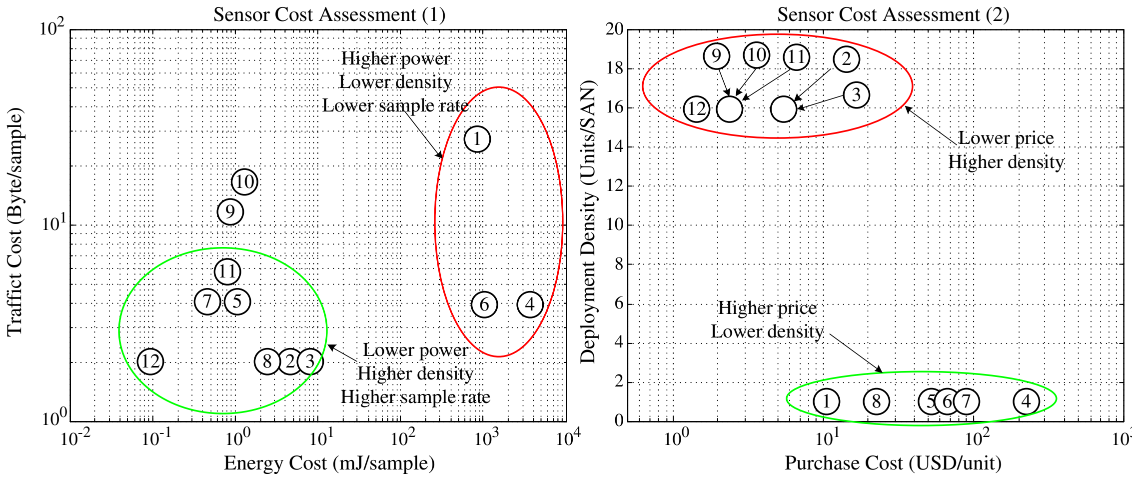


Fig. 7 Sensor cost comparison (the circlet number refers to the item number in Table 4)

16 SNs). More details of Main Node and Sub Node implementation are introduced in section 5.1.

4 Information fusions

4.1 Hierarchical information fusion architecture

The modern EIS must turn huge amounts of raw data into smart and timely decisions to deliver better products and services, and thus business intelligence (BI) techniques are demanded to extract useful information from oceans of data and deliver the useful information for decision-making (Duan and Xu 2012). In IoT enabled FSC solutions, the added values are delivered to users by providing useful information. Different users need the information to be delivered in different format, through different media, with different timing, and at different places. Moreover, users often have also different approach to make use of such information to support their decision making, so the information should be delivered in different level of abstraction. For example, consumers need the most straightforward expression of food quality and shelf life to decide "whether to buy or not" and "how much it is worth". But the enterprises, such as food dealers, need much more. First of all, they need location and identification of items to trace and manage the inventory; they also need real time alarming for accidents so as to reduce loss by timely treatment; additionally they need to predict shelf life and adjust purchase or deliver plan if needed; etc. Obviously the information from one individual sensor is incomprehensive for above purposes and thus information fusion is necessary.

We propose the hierarchical information fusion architecture (HIFA) as shown in Fig. 8. It includes a process of intelligently transforming the sensors' data into usable decision supporting information for various users, and another process of updating the intelligence of the system by collecting feedbacks from users. The close-loop nature enables self-learning ability of the system. Three levels of information fusion are supported in HIFA: in-cloud, in-system and on-site. A three-level data processing model was firstly proposed by Voisard and Ziekow (2010) for smart sensor event processing infrastructures to make best trade-offs among even treatment timing, traffic load and computation complexity. The core principle of the designed trade-offs is that: more timing critical events need to be closer to sensors and should be processed in lower complexity and lower traffic load. Here we have extended the model to a much larger scale: from on-site sensor nodes to the global FSC. The main functionalities are briefly described below. As the communication architecture is the essential design constraint for information fusion, the communication architecture is also briefly presented in Fig. 8. But the detailed introduction of communication architecture is out of the scope of this paper.

4.1.1 On-site information fusion

The raw data collected by sensors are firstly processed by the sensor nodes (MN and SN). Most time critical events are detected and notified to users by the alarming message. This message is generated by MN on-site and transmitted through wide area communication link between MN and user interface (e.g. mobile phone). Latency is minimized by eliminating the intermediate processes of an enterprise information system (EIS) (expect event logging that does not affect end-to-end latency). It is suitable to handle second level basis events. Limited by the computation and energy

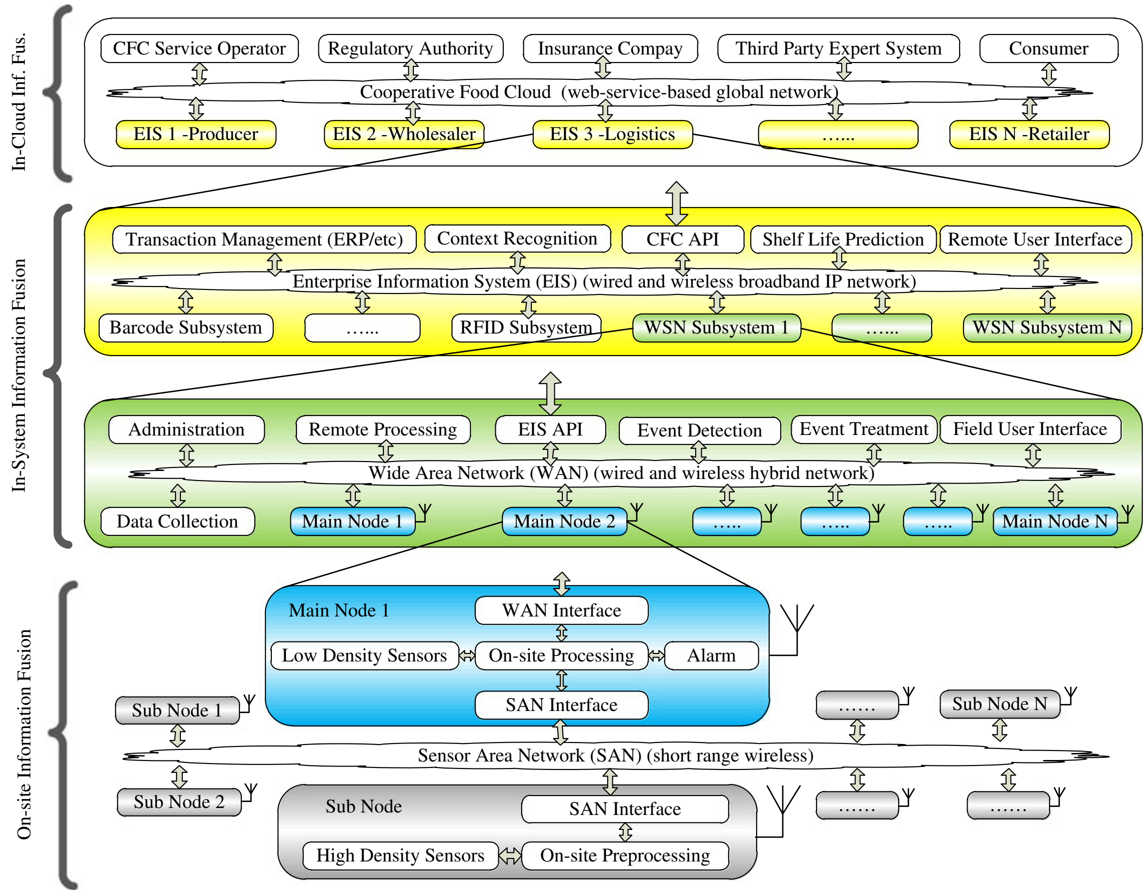


Fig. 8 The proposed hierarchical information fusion architecture (HIFA)

resources of sensor nodes, only basic data processing algorithms are available in this level. Moreover, the data processing algorithms are usually partitioned among MN and SN, i.e. lower complexity pre-processing in SN and other processing in MN. A typical example is the acceleration data processing that will be described in next sub-sections.

4.1.2 In-system information fusion

This refers to the information fusion within the EIS internally. The WSN subsystem, along with other key elements, is integrated into the EIS typically through hybrid broadband IP network. Message delivery latency is longer than that in on-site level due to the cross subsystem nature. So it is more suitable to handle minute basis events. As the information exchange happens with the enterprise, the interface among subsystems, so-called EIS-API, can be proprietary. In this level, the high complexity of sensor data processing and event detection is performed on the servers of WSN subsystem remotely.

Close-loop event capture and treatment helps users to handle all kinds of emergencies, which is much more valuable than the open-loop monitoring. Different treatment strategies are supported such as fully automatic treatment, fully manual treatment, and hybrid treatment. In particular, the event detection service collects data from sensors and shelf life from shelf life prediction service; then based on predefined event trigger and combination logic (e.g. "Temperature>30 °C AND Shelf Life<24 h"), it produces event notifications to the even treatment service; the latter takes predefined actions (e.g. "Start refrigerator"), and/or issues an alarming message (e.g. "Temperature too high!") to the user. All events and treatments are recorded to the event database as daily logs.

Context-awareness and self-configuration are also provided in this level. Due to the complexity of FSCs, the system must be dynamically and automatically reconfigured to adapt changeable surroundings. For example, for a sensor node installed in a container, its sensing targets and alarming conditions should be different when different types of products are transported. The sampling intervals may also be adjusted, e.g. using higher sampling rate at loading/unloading spots where damage possibility is higher. E.g. by combing with information from RFID, barcode and enterprise resource planning (ERP) subsystems, contexts of the objects that are being monitored are recognized by the WSN subsystem. The contexts may include location, food type, operator, transportation type, surrounding environment, etc. They are important to parameterize the event detection algorithms and event treatment services. Daily FSC logs are created and recoded in this level too. Another example is the shelf life prediction that will be discussed in detail in next sub-sections.

4.1.3 In-cloud information fusion

The latest progresses in cloud computing have provided powerful technologies to tear down barriers among enterprises. Information smoothly and safely flows across the physical and geographical boarders of all business entities throughout the value chain. In another word, cooperative business networks will be established in the global scale. Li et al. (2012) have proposed the framework to integrate hybrid wireless networks, typically WSN and RFID, into the cloud based EIS. In such systems, Web services over IP infrastructures are the cross-enterprise information exchange interfaces (Shin et al. 2011). Based on similar considerations, we propose a global scale Cooperative Food Cloud (CFC). All stakeholders mentioned in previous sections are connected. A new role of CFC Service Operator is recommended to work as the platform owner and be responsible for maintenance. The operator should be widely accepted by the whole value chain. Thus authorization from public sectors (e.g. regulatory authority) and non-profit are the key features. Additionally, information exchange with third party expert systems (e.g. for food engineering, public safety, supply chain operational research) are also supported. Due to complex authentication procedure, data translation, and maybe service fees, information traffic should be minimized. On the other hand, message latency is larger than that in other two levels. Examples are introduced in next subsections regarding the supply chain adjustment and shelf life prediction aided by expert systems.

4.2 On-site information fusion

We take the acceleration data processing as an example of the on-site information fusion. Technical details are described below.

4.2.1 Data characteristics

Mechanical damages are caused when acting forces exceed the tolerance limit of the package and goods. Some typical scenarios of acting forces are shown in Fig. 9 including vibration, tilt, and shock. The minimum forces tolerance of cargos and packages, and the maximum allowed accelerations in different transport types have been specified in some regulations as shown in Table 5. The values should be combined with static gravity force of 1.0 g (1 g=9.8 m/s^2) downwards. For example, when 0.7 g downward acting force is applied, the total acceleration that the goods are standing should be 1.7 g downward. Actual acceleration of the container should be carefully constrained within these limits. Otherwise, serious mechanical damages may happen due to the crash of packages.

We have analyzed the acceleration characteristics of data from a 46 day field test (see section 5 for details). 3-axis acceleration data was continuously sampled at 20 Hz, 8 bit resolution, ±4 g full scale and 79,397,600 samples (238,192,800 bytes) of raw data were collected. The field test covered all above three transportation types. To save time, we pick out 11 h data a test set. This test set covers container handover between trucks and ships, and thus the risk of damage is larger than other moments.

From the time domain waveform in Fig. 10 (a), we can see three main components: a Tilt Component corresponding to slow tilt changes, a Shock Component corresponding to sharp pulses caused by sudden shocks, and a Vibration Component corresponding to periodic and continuous vibration (probably caused by the wheels, engines, gaps of rail, wind and wave). The frequency domain analysis in Fig. 10 (b) shows that, most energy of acceleration is concentrated to the Tilt Component and two Vibration frequencies 1.95 Hz and 3.91 Hz. The amplitude distribution in Fig. 10(c) shows that, the data are narrowly centered on Tilt Component, except for the points where shock or tilt changes happen. From the users' point-of-view, the Shock Component is the most important information because it implicates potential damage spots. The Tilt Component is also necessary for users because it presents long term forces and postures of the package. In some cases, unexpected tilt changes may forecast potential collapses, drops and even traffic accidents. The Vibration Component is a supplementary to evaluate vehicle situation and external conditions like road flatness or sea wave height, but it occupies the majority of data amount.

4.2.2 Tilt, vibration and shock extraction

The Tilt Component is expressed by a discrete-time 3-axis vector **TLT(n)**=[$TLT_x(n)$, $TLT_y(n)$, $TLT_z(n)$], where n is the index in the measurement sequence. **TLT(n)** is an average of the raw data **A(m)**=[$A_x(m)$, $A_y(m)$, $A_z(m)$], where m is the index in the raw data sequence. **A(m)** is firstly filtered by an infinite impulse response (IIR) filter producing **A'(m)** by (3) where β is a natural

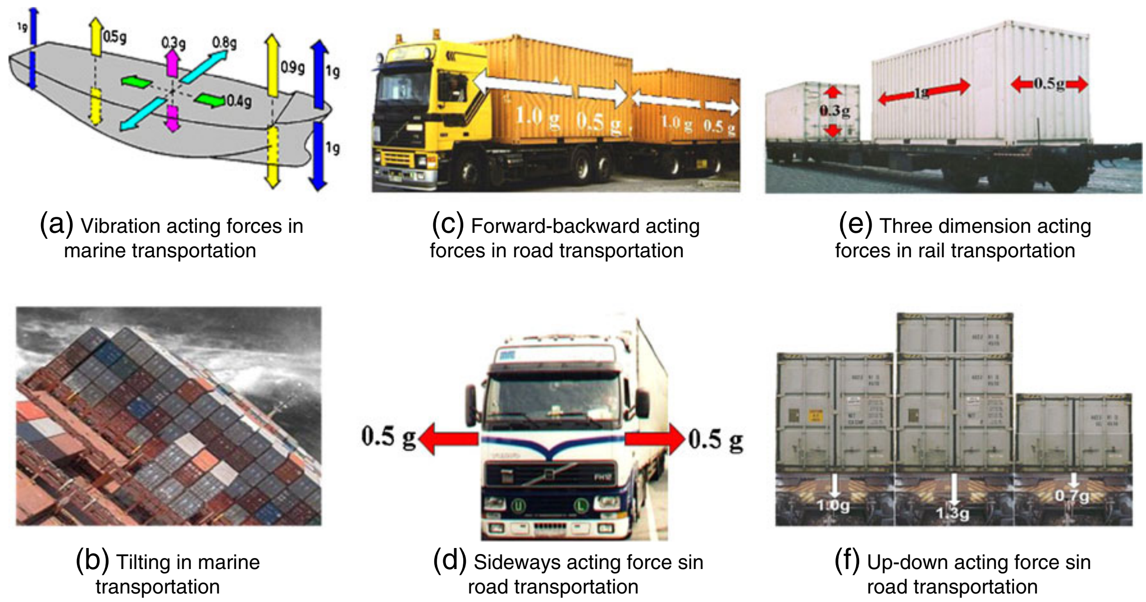


Fig. 9 Scenarios of acting forces in transportation (g is the gravity acceleration, 1 g=9.81 m/s^2) (German Insurance Association 2002–2011). **a** Vibration acting forces in marine transportation. **b** Tilting in marine transportation. **c** Forward-backward acting forces in road transportation. **d** Sideways acting forces in road transportation. **e** Three dimension acting forces in rail transportation. **f** Up-down acting forces in road transportation

number to determine the filter bandwidth. Then **A'(m)** is resampled into **TLT(n)** by (4) where T_{raw} and T_{tilt} are sampling intervals of **A(m)** and **TLT(n)** respectively.

$$\mathbf{A}'(\mathbf{m}) = \begin{cases} \mathbf{A}'(\mathbf{m}-\mathbf{1}) - \dfrac{\mathbf{A}'(\mathbf{m}-\mathbf{1})}{2^{\beta}} + \mathbf{A}(\mathbf{m}), if\, m \neq 0 \\ 0, if\, m = 0. \end{cases} \tag{3}$$

$$\mathbf{TLT}(\mathbf{n}) = \frac{\mathbf{A}'(m)}{2^{\beta}}, when\ n^{*}\ T_{tilt} = m^{*}\ T_{raw} \tag{4}$$

The Shock Component is expressed by four counters including the vector **SHK(q)**=[$SHK_x(q)$, $SHK_y(q)$, $SHK_z(q)$] and the scalar *TIM(q)*. **SHK(q)** refers to the number of detected shock events in 3-axis. *TIM(q)* refers to the number of raw data samples since the moment when the **SHK(q)** and *TIM(q)* counters start, where q is the index in the measurement sequences. These four counters restart once the current measurements are read out, which indicates the current statistic period has finished and a new period will start. The statistic period doesn't have to be even, instead, upper level software determines when to read the statistic results without missing any shock events. The shock event is defined in (5) where the **SEI(m)** is the shock event indicator, and **SDT**=[SDT_x, SDT_y, SDT_z] is the 3-axis shock event detection thresholds defined by upper software. The **SHK(q)** counters are desscribed in (6).

$$\mathbf{SEI}(\mathbf{m}) = \begin{cases} 1, \text{if} \left| \mathbf{A}(\mathbf{m}) - \dfrac{\mathbf{A}'(m)}{2^{\beta}} \right| \geq \mathbf{SDT} \\ 0, \text{else} \end{cases} \tag{5}$$

$$\mathbf{SHK}(\mathbf{q}) = \begin{cases} \sum_{m} \mathbf{SEI}(\mathbf{m}), \text{if in current statistic period} \\ 0, \text{in new statistic period starts} \end{cases} \tag{6}$$

The Vibration Component is also expressed by a vector **VBR(p)**=[$VBR_x(p)$, $VBR_y(p)$, $VBR_z(p)$] where p is the index in the measurement sequence. It is calculated by (7)–(9) where |•| refers to the absolute value function, γ is the filter bandwidth

Table 5 Maximum accelerations allowed in different transportation systems (German Insurance Association 2002–2011)

Transport type	Forward	Backward	Sideways	Downward	Upward
Marine	0.8 g	0.8 g	±0.8 g	1.0 g±1.0 g	−1.0 g±1.0 g
Rail	1.0 g	0.5 g	0.5 g	1.0	−1.0 g
Road	1.0 g	1.0 g	0.5 g	1.0±0.3 g	−1.0 g±0.3 g

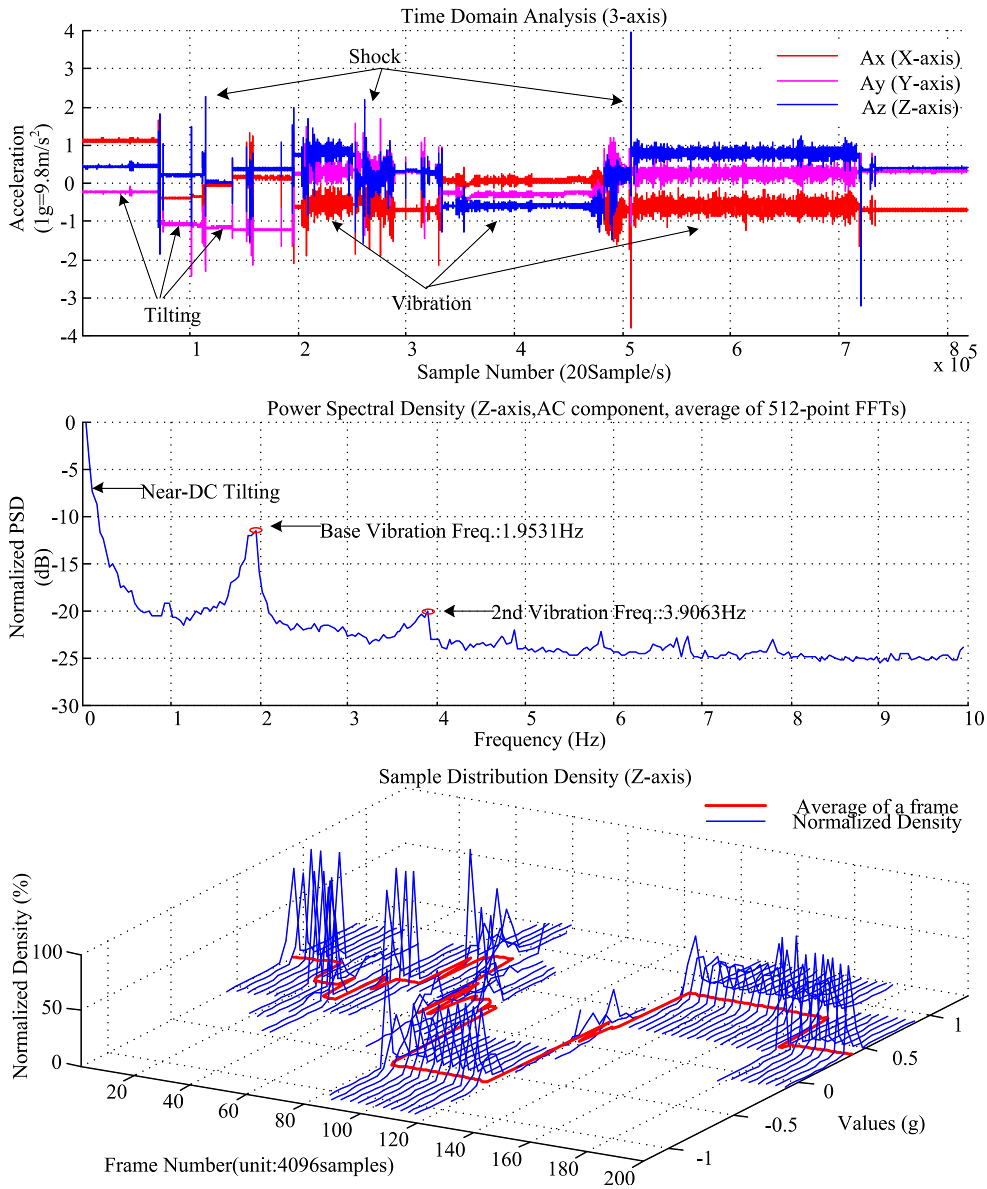


Fig. 10 Characteristics of acceleration data of the 11-day test set

factor, and T_{vbr} is the sampling interval of vibration data. Note that, all the operations upon vectors (including **TLT(n), SHK(q), VBR(p), A(m), A'(m), SEI(m), $\mathbf{V_{abs}}$(m), $\mathbf{V_{abs}}$'(m),** and **SDT)** should be done in three axes separately.

$$\mathbf{V_{abs}}(\mathbf{m}) = \begin{cases} 0, \text{if} \mathbf{SEI}(\mathbf{m}) \neq 0 \\ \left| \mathbf{A}(\mathbf{m}) - \dfrac{\mathbf{A}'(\mathbf{m})}{2^{\beta}} \right|, \text{if} \mathbf{SEI}(\mathbf{m}) = 0 \end{cases} \tag{7}$$

$$\mathbf{V_{abs}}'(\mathbf{m}) = \begin{cases} \mathbf{V_{abs}}'(\mathbf{m}-\mathbf{1}) - \dfrac{\mathbf{V_{abs}}'(\mathbf{m}-\mathbf{1})}{2^{\gamma}} + \mathbf{V_{abs}}(\mathbf{m}), \text{if} \mathrm{m} \neq 0 \\ 0, \text{if} \mathrm{m} = 0 \end{cases} \tag{8}$$

$$\mathbf{VBR}(\mathbf{p}) = \frac{\mathbf{V_{abs}}'(\mathbf{m})}{2^{\gamma}}, \text{when } p^{*}\, T_{vbr} = m^{*}\, T_{raw} \tag{9}$$

4.2.3 Implementation and result

The above algorithms are implemented on both MN and SN. In MN, all three components are calculated. In the SN which is of lower performance and less energy, only shock and tilt components are calculated and transmitted. The algorithms have been verified by the field test data and results are shown in Fig. 11. In this test, the parameters we use are β=10, T_{raw}=50 ms, T_{tilt}=600 s, γ=12, T_{vbr}=600 s, the **SHK(q)** and *TIM(q)* statistic period is 600 s, and **SDT** is set to [0.4 g, 0.4 g, 0.4 g]. We can see that, the proposed algorithms can effectively recognize shock events and measure vibrations and tilts. The extremely large amount of raw data is efficiently reduced by higher level information extraction. The extracted **TLT(n), SHK(q)** and **VBR(p)** are

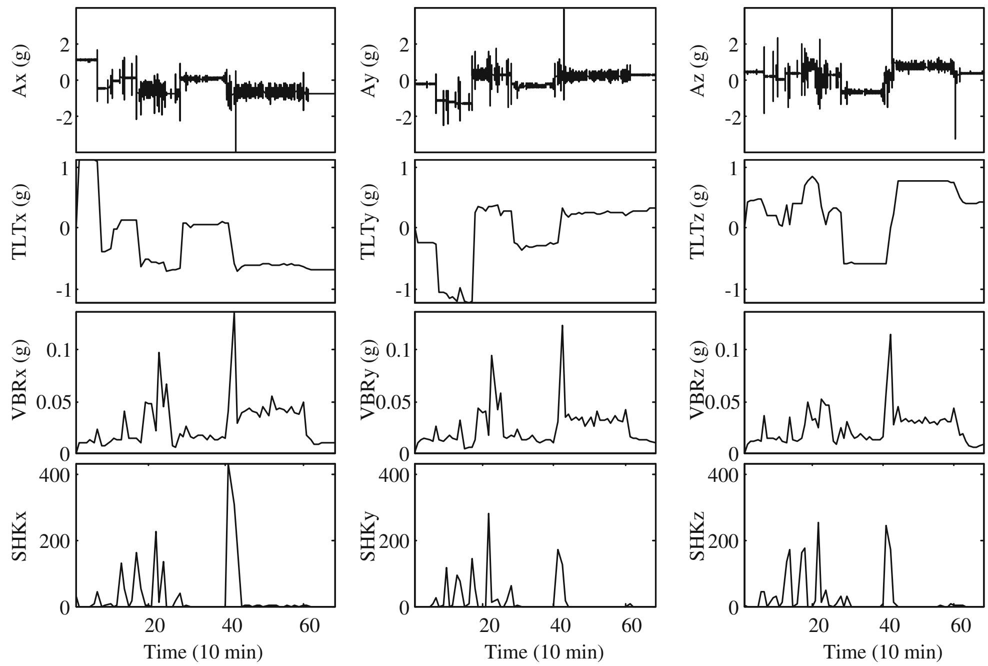


Fig. 11 Results of acceleration data processing when applied to the 11-day test set

directly usable to evaluate the transportation quality and risk of mechanical damages. Moreover, the proposed algorithms are easy to implement on resource constrained sensor nodes due to low complexity. The division operations in (3)–(5) and (7)–(9) are actually implemented by right-shift operations because the divisors are power of 2. At the same time, the operations applied to every raw data **A(m)** including filtering and accumulation are done immediately when the raw data are sampled, and after that the raw data can be discarded. There is no need to store a sequence of **A(m).** So the memory footprints are as small as other sensor sources. Considering the effect of word-length in fixed-point microcontrollers, limiting operations are necessary to prevent the overflow of accumulators (e.g. **A'(m)** and $\mathbf{V_{abs}'(m)}$). In our implementation where the accumulators use 32-bit integer type and raw data **A(m)** use 12-bit integer, the accumulators can work for at least 14 h without being limited. So the negative effect of such limiting operation is negligible.

4.3 In-system information fusion

We take the shelf life prediction as an example of in-system information fusion. Technical details are described below. The shelf life prediction is a close-loop process where the user's feedback is essentially useful for self-calibration and self-learning. In particular, the shelf life prediction service collects data from sensors and queries the shelf life prediction databases; then it delivers estimated shelf life information to the user, and collects feedback from the user. It is also in charge of feedback validation to make sure only qualified feedback could be recorded in the databases.

4.3.1 Question formulation

The shelf life (L) of food product is defined as the duration from the present moment to the moment when it reaches the lowest acceptable quality or reaches the highest acceptable spoilage. These two expressions are essentially equal, so in this paper we use a universal term "quality index" to describe the both cases unless specially stated. As shown in (10), the quality index Q is defined as a function of time t and environmental conditions *E(t)*. *E(t)* is a set of potential environmental factors that could affect the quality index over time. *E(t)* may include temperature *T(t)*, humidity *H(t)*, carbon dioxide concentration *CO2(t)*, oxygen concentration *O2(t)*, ethylene concentration *Eth(t)*, etc. As the environmental conditions are dynamic, the model in (10) is so called *Dynamic Model*. As a special case, when the environment conditions are static throughout the observation period, model (10) could be simplified into (11) (so-called *Static Model*). Obviously the model defined in (10) is related to s specific type of food product.

$$Q(t) = f[t, E(t)], \text{where} E(t) = \{T(t), H(t), CO2(t), O(t), Eth(t), \ldots\} \quad (10)$$

$$Q(t) = f[t, E], \text{where } E = \{T, H, CO2, O, Eth, \ldots\} \quad (11)$$

As shown in Fig. 12, the task of shelf life prediction at t_x (so-called the Work Point), is to derive the remaining life time L_x from t_x to t_e (so-called the End Point). At t_e the quality index reaches to the end level Q_e. Before the Work Point, the initial quality Q_b is measured at the Begin Point (t_b).

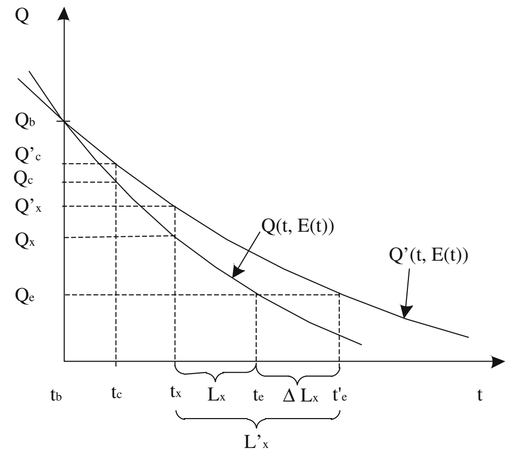


Fig. 12 Formulation of shelf life prediction question

A series of historic environmental conditions $\{E(t_c)\}$ are collected at Check Point $\{t_c\}$. So the shelf life prediction question can be formulated as (12).

$$\{Q_b, t_b, \{E(t_c)\}, E(t_x), \{t_c\}, Q_e, t_x\} \xrightarrow{Q'(t,E(t))} \{L_x\} \tag{12}$$

In practices, considering the errors in theoretical models, above estimation can only be based on an approximate curve *Q'(t, E(t))* instead of ideal curve *Q(t, E(t))*. Correspondingly, the estimated shelf life is denoted as L'_x. The estimation error $\Delta L_x = L_x - L'_x$ exists and should be minimized. Furthermore, the value of *E(t)* is not really predictable when $t > t_x$. An acceptable approximation is to assume the environmental conditions will keep the same as the Work Point. So question (12) is re-expressed as (13). It is a set of non-linear functions with multiple variables.

$$\{Q_b, t_b, \{E(t_c)\}, E(t_x), \{t_c\}, Q_e, t_x\} \xrightarrow{\begin{cases} Q'(t,E(t)), if\, t < t_x \\ Q'(t,E(t_x)), if\, t \geq t_x \end{cases}} \{L'_x\} \tag{13}$$

As the t_b, $\{t_c\}$, t_x, $E(t_x)$ and $\{E(t_c)\}$ are collected by the IoT system, the left of the shelf prediction question is split into four sub-questions.

- SQ1: to quantize the quality index Q
- SQ2: to determine the end quality index Q_e
- SQ3: to model the quality index curve *Q'(t, E(t))* with minimized estimation error ΔL_x
- SQ4: to resolve the function set of (13)

4.3.2 Modeling and challenge

Many studies have been done on above sub-questions. In Table 7, some of the newest results are collected and compared in subject to SQ1~SQ4. We could summarize that:

- Corresponding to SQ1, the selection of quality indexes and methods to quantize them are diverse;
- Corresponding to SQ2, the definitions of end quality index are diverse;
- Corresponding to SQ3,

  – all existing models follow the Arrhenius' law (Chang 1981) in kinetics to describe the effect of temperature;
  – the effect of temperature is studied the most but models for modified atmosphere preservation (MAP) conditions like carbon dioxide and oxygen are rare and diverse
  – models to describe the effect of other parameters like humidity, vibration, shock, ethylene, etc, are even rarer;
  – models of *Q'(t, E(t))* are diverse no matter considering the complexity of E(t) or not.

Obviously, it is very difficult to integrate such diverse analytical models of all kinds of products in the lightweight wireless sensor devices (Jedermann et al. 2011). The only feasible solution is to implement at the in-system level. The EIS can seamlessly integrate existing models as well as keep improving by means of self-learning.

4.3.3 Self-learning approach

The analytical models are converted into discrete numerical models and stored in the quality database (QDB). For every value in QDB, the system maintains a confidence coefficient to describe its reliability, the higher the better. The confidence coefficients are stored in the confidence coefficient database (CDB). Both QDB and CDB are an array of $K+2$ dimensions where K is the number of environmental conditions supported by the numerical models. Among the $K+2$ dimensions, the first dimension is time t; the second dimension is the type of product *Type*; and other K dimensions are the environmental conditions *Condition*. So the values in QDB and CDB are indexed and accessed through a coordinate of (t, *Type*, $Condition_1$, ... , $Condition_K$), where $Codition_1$ and $Condition_K$ are the 1st condition and kth condition respectively. The resolution t and quantization steps of *Condition* are the trade-offs between accuracy and computation load.

As shown in Algorithm 1, the databases are initialized when the system is firstly established. The work in this step is to collect as many as possible analytical models, and then quantize them with sufficient resolutions. If a particular value in QDB cannot be derived from any existing models, it is set to NULL. All values in CDB are set to 0 during initialization, which means the values in QDB are not trusted as they have not been verified in practice yet.

Algorithm 1 Initialization of databases

```
Function Initialize (K0, TypeList0, Q'(t, Condition))
K=K0;//K0 is the maximum number of conditions supported by existing models
TypeList=TypeList0;//list of product type supported by existing models
CreateDatabase (QDB, K+2); //create database of (K+2) dimensions
CreateDatabase (CDB, K+2); //create database of (K+2) dimensions
for Type in TypeList
   for Condition in ConditionList (Type) // list of supported E(t) of this product type
      if Q'(t, E(t) ) != NULL
         QDB(Type, t, Condition) = Q'(t, Condition);//using existing models
         CDB(Type, t, Condition) = 0;// not trusted
      else
         QDB(Type, t, Condition) = NULL;// invalid as model not available
         CDB(Type, t, Condition) = 0;//not trusted
      end if
   end for
end for
```

Then the system starts working. The data in databases are queried and calibrated as described by Algorithm 2. Besides a coordinate of (t, $Type$, $Codition_1$, ... , $Condition_K$), a request command may carry an optional feedback Q_x referring to the measured quality index at the Work Point. If a valid Q_x is carried by the request, the system can use it in three ways. One is to increase or decrease the CDB value according to the error between the Q'_x from QDB and Q_x from user. The second way is to calibrate the values in QDB according to specific strategy. The third way is to add the Q_x into QDB if there is no matching

Algorithm 2 Query and calibration of databases by self-learning

```
Function Query (Typex, Conditionx, tx, Qx)
//Qx is the optional user feedback
if (Type in TypeList) AND (Condition in ConditionList (Type))
   if Qx is NULL
      if QDB (Type, tx, Condition) is NULL
         QDB (Type, tx, Condition)= approximate(QDB, CDB, Type, tx, Condition);
         CDB(Type,tx,Condition)=0;
      end if
      return QDB (Type, tx, Condition), CDB(Type, tx, Condition);
   else if |QDB (Type, tx, Condition) – Qx|<ErrorThreshold
      CDB(Type, tx, Condition) = CDB(Type, tx, Condition) +1;//increase confidence
   else      //calibrate database by user feedback
      CDB(Type, tx, Condition) = CDB(Type, tx, Condition) -1;//decrease confidence
      QDB(Type, tx, Condition)=calibrate(QDB(Type, tx, Condition), Qx);
   end if
else
   if (Qx is NULL)
      return NULL;
   else
      if (Type not in TypeList)
         AddTypeToDatabase (QDB);
         AddTypeToDatabase (CDB);
      else
         AddConditionToDatabase (QDB);
         AddConditionToDatabase (CDB);
      end if
      QDB(Type, tx, Condition) = Qx;
      CDB(Type, tx, Condition) = 0;
   end if
end if
```

product type or no matching condition. In these ways, the shelf life prediction models are extended by self-learning. Higher accuracy and reliability could be achieved when it gets more raw data from field and feedback from users. Additionally, if no matching values are found in databases, alternative approximation can be derived by interpolation.

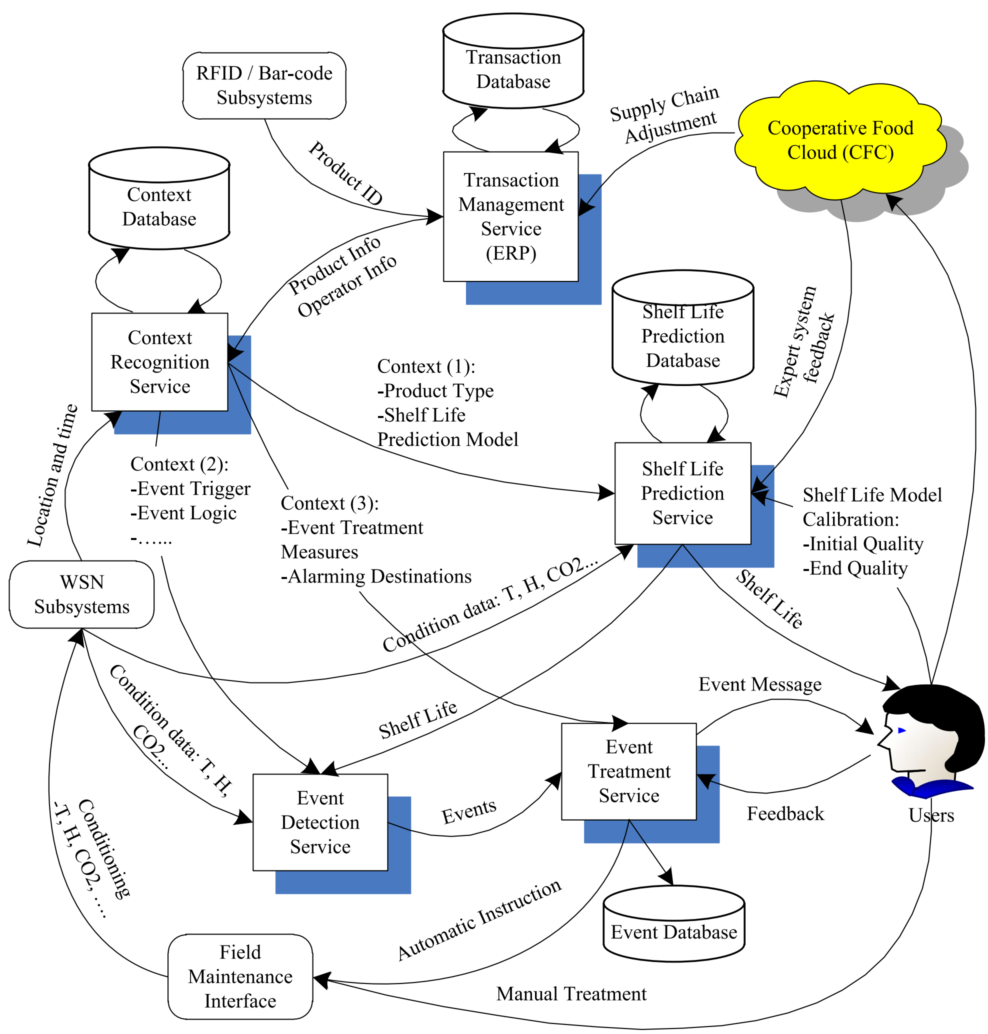
The algorithms themselves do not require to be performed in the backbone system. If the sensor nodes are equipped with distributed data base system and have enough memory and processing capacity, it is possible to run a part of this shelf life prediction on-site. Some preliminary results have been introduced by Jedermann et al. (2011). However, the synchronization of databases may cause a mass of communication between the sensor nodes and backbone system.

4.4 In-cloud information fusion

In-cloud information fusion is usually an extension of corresponding in-system functionalities. For example, if available, some third party expert systems on food quality engineering could be linked to the self-learning approach. For Algorithm 2, the difference is to replace the user's feedback by the feedback from the expert systems. Some typical in-cloud and related in-system information fusions are illustrated in Fig. 13.

Another the typical in-cloud information fusion is the real-time supply chain re-planning. The enterprises that are involved in one FSC can share the real time monitoring and tracking information. When accident happens, e.g. unexpected spoilage due to low quality transportation, the product owner can make real time adjustment to the supply chain plan. They can start from shelf life prediction to know the deadline that the product must be sold. Secondly, they check a transaction processing systems within enterprise systems (ES) to get the newest requirements from downstream enterprises. Thirdly they choose the most suitable possible new recipient according to the location of current batch. Then a new round of transaction negotiation can be initiated automatically through the established CFC services. All potential new recipients will receive this request and give response. New transaction can be reached based on some discount to the new recipient and compensation to old recipient. Benefits to all parties can be optimized by cooperative business logic that is predefined in

Fig. 13 In-cloud and in-system information fusion workflow



the CFC conditions. In this procedure, some third party expert systems are also hopefully available to optimize the operations.

5 Implementation and field tests

5.1 Sensor nodes

Hardware devices including the MNs and SNs have been manufactured. As shown in Fig. 14, the Main Node comprises 4 modularized PCB boards: Main Board, Interface Board, Sensor Board and SAN board. The Sub Node comprises 1 PCB board and a pair of button batteries. The Main Node is assembled with a 4000 mAh rechargeable Li-ion battery inside a water proof 188 mm*65 mm* 26 mm aluminum case. The Sub Node is powered by a pair of 500 mAh Li-ion cell batteries, and enclosed in a water proof 86 mm*54 mm* 6.0 mm engineering plastic case.

On the Main Board, we choose MSP430F1611 from Texas Instruments Inc. as the MCU and GSM/GPRS chipset from Mediatek Inc. for GPRS communication. A Micro-SD card is integrated as large local storage. A real time clock (RTC) is used to keep precise time synchronization without waking up the MCU frequently and has significantly reduced system power consumption in sleep mode. Full system power management functions are realized, including Li-ion battery charging, battery voltage and current monitoring and power switching module-by-module and sensor-by-sensor. The Sensor Board consists of a set of heavyweight sensors including the carbon dioxide sensor, oxygen sensor, ethylene sensor, and GPS sensors. The soil moisture sensor, hydrogen sulfide sensor, and light sensor are supported through external plugins due to structural limitations. Small signal handling circuits associated with sensors including bridges, filters, instrument amplifiers and offsets or reference voltages are carefully tuned to ensure the accuracy and linearity of sensors. In the Sub Node, the MCU is MSP430F2132 from Texas Instruments Inc. which is less powerful but cheaper than that used in the Main Node. Sub Node uses the same RTC chip as Main Node. A 512 Mb EEPROM is used as local storage. The lightweight sensors including the temperature sensor, humidity sensor, and accelerometer are integrated in both Main Node and Sub Node. The communication between Main Node and Sub Node is realized through 2.45 GHz low power transceiver. More details about the communication architecture, protocols, firmware, and back bone systems are available in our previous works (Pang et al. 2009 and 2010).

5.2 System software

5.2.1 User interface

Two types of user interfaces (UI) have been implemented as shown in Fig. 15. The UI for enterprises is enabled by Asynchronous JavaScript and XML (AJAX) and provides the

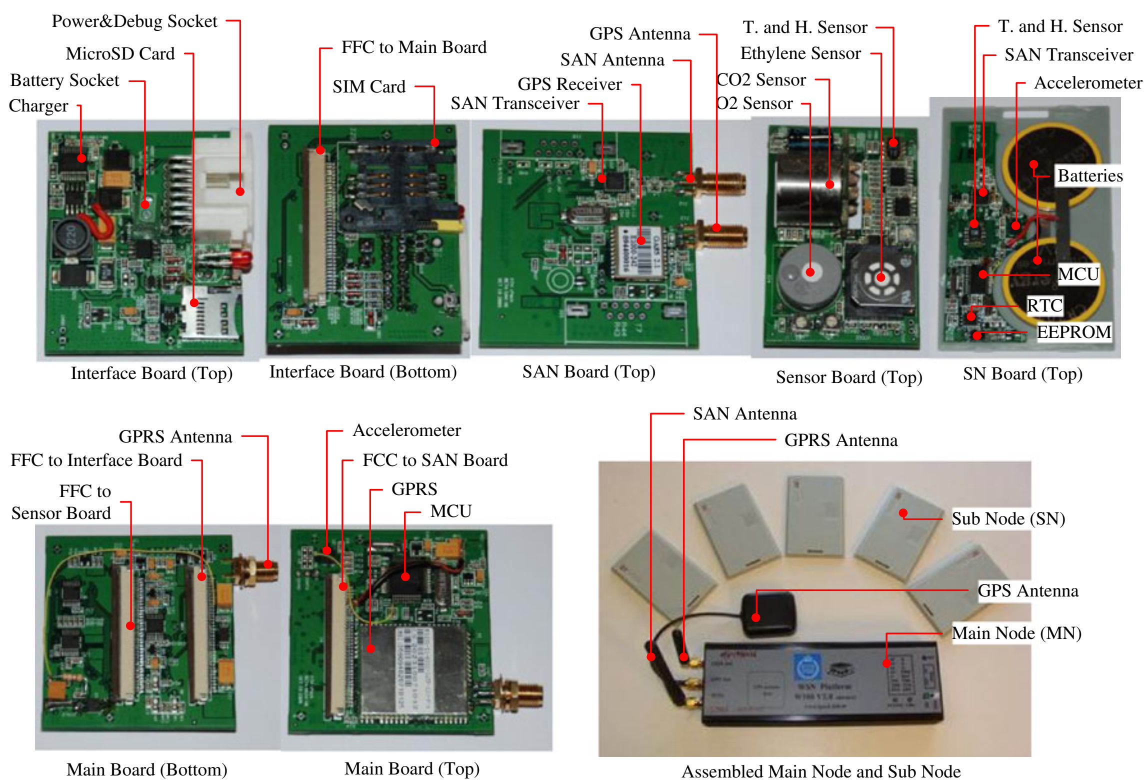


Fig. 14 Implemented sensor nodes

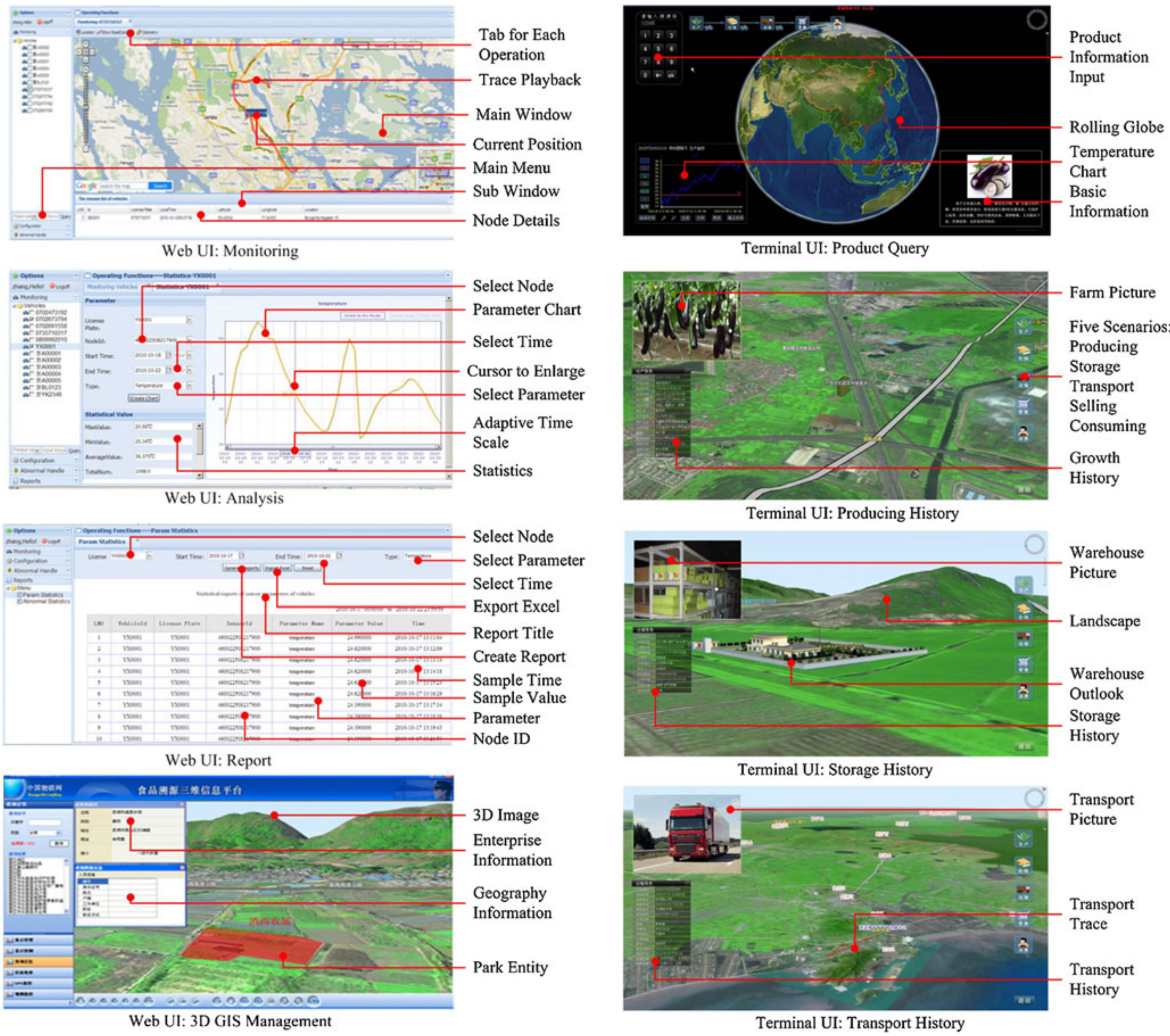


Fig. 15 Web-based user interfaces for enterprises (*left*) and consumers (*right*)

technical view of sensor data, fleet management, WSN management, data analysis, report creation and user management functions. The UI for consumers is based on 3D-GIS (three dimension geographic information system) technology which provides a vivid and impressive view of data collected across the entire food chain. Consumers can browse all historic data of a particular food product through the touch screen. Dedicated pages are designed for the five scenarios. For example, the UI page for the Transport scenario comprises a picture of vehicle, a list of product information, a transportation tout in 3D map and sensor data charts of different places.

5.2.2 Server and database

The server software (Fig. 16) is based on MySQL5.5.12 database management system which runs on Microsoft Windows with the supporting of .NET Framework 4.0. In the server, the TCP packets from MNs are passed by a TCP Service; the control and configuration commands from server to MNs are handled by a SMS Service; the UI requests from UIs are handled by a set of Web-based 3D-GIS services. More details are available in our previous work (Pang et al. 2012).

5.3 Field tests

5.3.1 Test setup

A field test was carried out to verify the system concept and implemented prototypes. In the field test, the sensor node was attached with the cargo during the delivery process along with a batch of yellow honeydew (Royalsweet^{TM} Brazilian melon, produced by Fazenda Agrícola Famosa

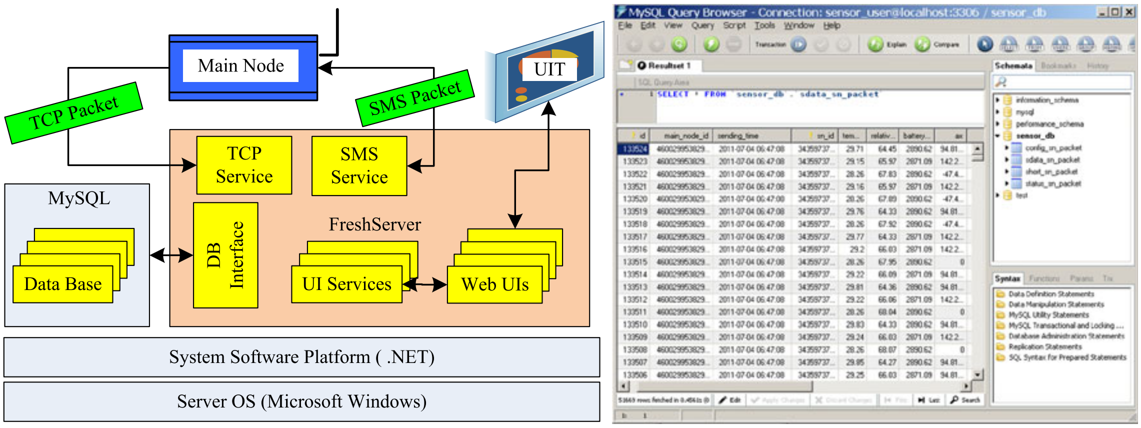


Fig. 16 Key elements in the server software (*left*) and MySQL management interface (*right*)

Ltda in Brazil). They were transported by Frankort & Koning BV from Icapuí Ceará, Brazil, via Venlo, Netherland, to Stockholm, Sweden (Fig. 17). The journey took 46 days in total. Throughout the whole transportation chain, the sensor node measured conditions in the environment including oxygen, carbon dioxide, ethylene, temperature, humidity, and mechanical stress like vibrations, tilts and shocks. The measurements are transmitted through the GSM network upon request or saved in a local storage if the network is unavailable. The backend software system monitors the environmental and mechanical conditions. If any variable is out of range, the device sends out alarms through a short message service (SMS) and reports the events to the database indicating time and positions. Through this system, the user can also establish direct communication with the sensor node for system configuration and maintenance purposes.

5.3.2 Sensor data

Measurement interval of the temperature, humidity, oxygen, carbon dioxide, and ethylene sensors are 1 measurement per hour, resulting in 1,107 samples from each sensor. The raw data sample rate of accelerometer is 20 samples per second, resulting in 79,397,600 samples in each axis. The measurement interval of extracted tilt, vibration and shock data is 1 measurement per 10 min, resulting in 6,616 samples for each axis. Due to the installation limits, the hydrogen sulfide sensor, light sensor and soil moisture sensor were not used in this test. The data sampled in the test are plotted in Fig. 18, as well as the results of context recognition. As the three axes of acceleration data show similar characteristics, we only plot the z-axis as an example. We did not collect valid ethylene concentrations during this field test. One reason is the ethylene produced by the honeydew is so little that it is always below the minimum detectable level of the sensor. E.g. the production rate of ethylene is at the level of 1 uL/Kg/hour, which means if 1 t fruits are enclosed in 1.0 m^3 air, after 1 h the ethylene concentration may reach 1 ppm (Jedermann et al. 2011). Another reason is the ethylene is not accumulated because the container is not sufficiently sealed.

5.3.3 Context recognition

From the plotted curves, we can recognize the main contexts through the logistic chain. For example, in context 3, the products are transported in Brazil by trucks. The vibration of temperature is synchronized with clock over day and night. This phenomenon

Fig. 17 The scenarios of sensor node placement in a container

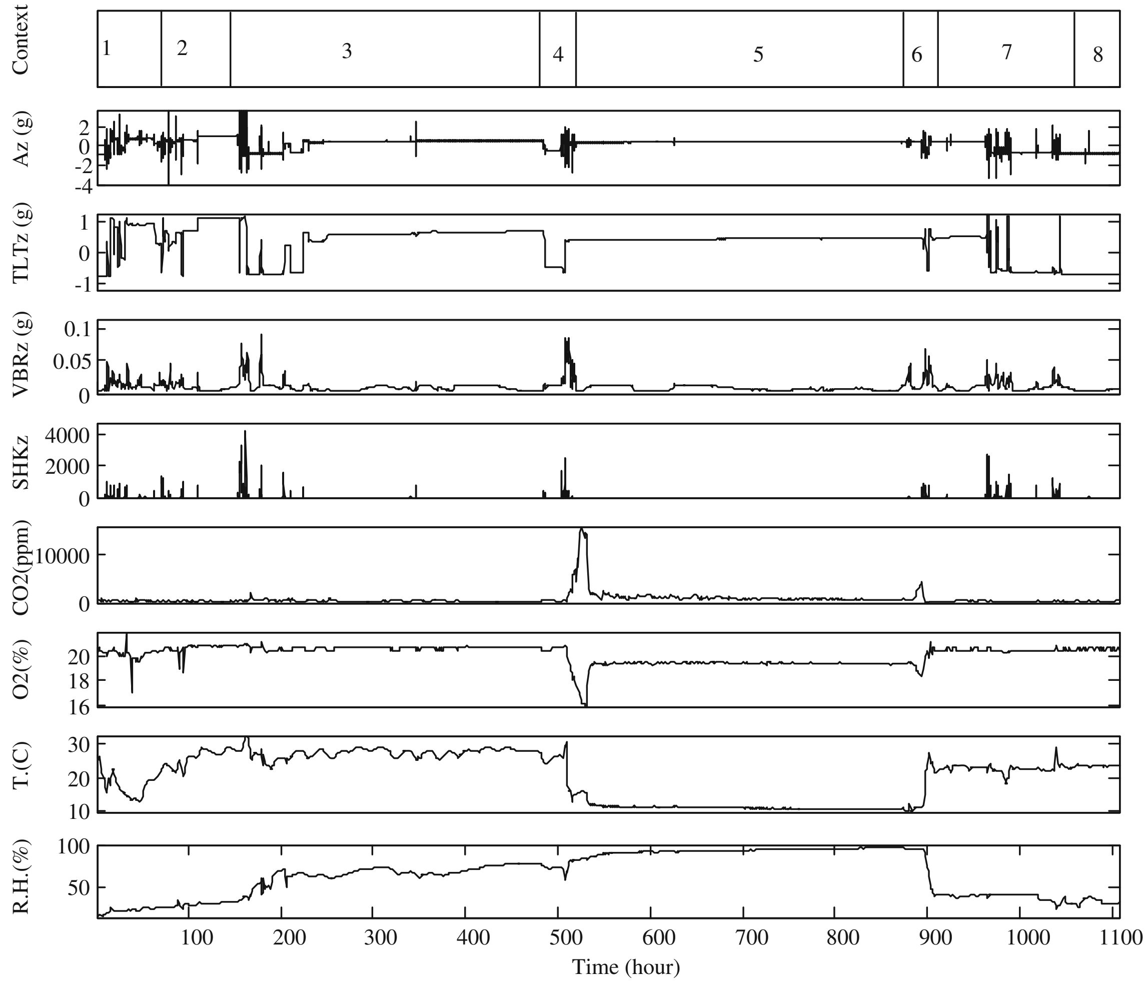


Fig. 18 Field test data analysis

confirms that the transportation is not refrigerated. The frequent shock events means that, the load/unload operations at some handover points are not sufficiently restricted. The rapid changes of tilt implicates that the sensor node, possibly as well as the fruit packages, are turned over time-to-time. In context 5 where the products are transported by ship, the environmental conditions appear more stable than those in context 3: the temperature is kept low by refrigerators but it spends 1 day to reach the expected temperature level, which is limited by the refrigerator's capacitance; the humidity increases gradually from 80 % to 95 % due to the evaporation of water in the honeydew; the oxygen concentration is lower than free air; the carbon dioxide rises; the container's posture is unchanged, and there is no noticeable shock except the continuous vibrations. When it reaches the context 7, transportation in Europe on road, the conditions become versatile again due to non-refrigerated containers, frequent handovers, and complicated traffic conditions.

5.3.4 Sensitive spots

Some sensitive spots in this supply chain are discovered where significant condition changes happen due to natural or human interferences. For example, in context 4 where the cargo is in port, sharp changes of oxygen and carbon dioxide are observed. It is possible that the fruits have been exposed to some exhaust gases. In such sensitive spots, environmental conditions become more critical and unpredictable, so the risk of damages increases. As a possible measurement, a higher sampling rate as well as a higher event treatment priority should be considered. Furthermore, the list of sensitive spots should be updated on a time basis by the newest event statistic.

5.3.5 Valuable information to users

Suggestions about how to improve transportation quality can be derived to the users involved in this food chain.

For example, it would be better if they could use better sealed cargos for road transport in order to keep the water in fruits. It would be even better if the temperature could be stabilized approximately to 10 °C by using refrigerated cargos or trucks in Brazil because it is a very hot and long journey from the farm to the port. Furthermore, human interferences and miss-handling should be reduced as much as possible at handover points like the ports I Brazil and Europe. And we believe that experts in food preservation and cold chain management areas could produce more valuable outcomes based on the information fusion mechanisms proposed in this paper.

5.3.6 Feedback from users

We have got very positive feedbacks from users. They have seen what has happened during the long journey for the first time. The data is provided in sufficient resolutions and accuracies. The high level information for decision making is valuable. Some improvement suggestions are also provided. Firstly, the hardware reliability needs to be improved. That is a fully water proof design is necessary as the condition in container is often near to 99 %. More context adaptive functionalities are needed. For example, they wish the MNs to start sending data via domestic GPRS network to server as long as it reaches the dock of Sweden. Meanwhile, the MNs should turn the GPRS communication once it goes out of Sweden because the international roaming is extremely expensive. This has also reminded us of another issue. To enable the globally available IoT service, the international data roaming cost should be reduced to reasonable level (e.g. at the same order as the domestic fee). This roaming fee should be looked as "geographical barrier" that we should tear down to welcome the era of IoT. Regarding the system software, they want a graphic UI through handhold devices, typically smart phone, besides the SMS interface that we have provided. Despite the issues mentioned above, the field trials have proven the key concept of this work.

6 Limitations

Currently we use a static sensor portfolio strategy in which the sensors in MNs and SNs are not changeable. It is determined when the solution is firstly specified in the value creation phase. However, a better approach so-called dynamic sensor portfolio is needed. In dynamic sensor portfolio, unrequired sensors and corresponding information fusion modules can be removed or deactivated from field devices and backend system. When needed, the sensors and fusion modules can be added or activated dynamically. Thus, the deployment complexity, maintenance cost, hardware cost, and hence user satisfaction, can be optimized. To do this, better modularized design not only in hardware but also in system software is essential. This concept has been applied in our new version system.

The value assessment framework proposed in this paper is limited by the data sources. The purpose of presenting the quantitative results in Table 2 is mainly to give a showcase rather than conclusive judgment. As the accuracy of results highly depends on the quality of market research, to enlarge the data sets especially by field surveys will be an important topic in the future. To refine the framework, more objective criteria such as return-on-investment (ROI) and gross-profit margin (GPM) may be considered to enhance the subjective criteria currently used.

The shelf life prediction algorithms have not been evaluated in field trials. A known issue is the convergence of the feedback mechanisms. The accuracy of possible interpolation algorithms needs to be evaluated further. Due to financial limitations, the scale of field trials is small and many functionalities of the prototype system have not been verified yet. Moreover, the bill-of-material (BOM) cost of the hardware is still too high when we talk about mass production. All these should be studied in the next steps of this ongoing project.

Finally, we would like to mention that, there are many technical challenges in the design of IoT solutions for FSCs. They include but not limited to low power design, energy harvesting, reliable communication, signal fading, global data roaming, backend system integration, standardization, etc. These challenges have been considered in our research project. But in this paper, we only focus on the value creation, sensor portfolios and information fusions. Other aspects will be discussed in future works.

7 Conclusions

The revolution of IoT technologies have brought out great potentials to make today's food supply chain safer, more effective and more sustainable. To catch the opportunities, the system paradigm must be extended from the traditional traceability-centric design to the value-centric design. In this paper, a systematic value-centric business-technology joint design framework is proposed and verified by a real solution as well as field trials.

To extend and consolidate the value base, we start from value creation and assessment which evaluates the added-values by a quantitative stakeholder analysis throughout the entire value chain involving consumers, enterprises and public sectors. More attractive "income-centric" added-values such as shelf life prediction, sales premium, precision agriculture, and reduction of assurance cost are highlighted beyond the conventional traceability. To deliver the "income-centric" values to users, the sensor portfolios and information fusions must correspond to the values created above. In this paper, comprehensive sensor portfolios are developed in a systematic way, by exploring causes of food spoilage, comparing available sensing technologies and products, and evaluating the energy and traffic costs. The three-tier information fusion architecture is proposed by mapping all data processing and information delivery functionalities into a global scale "*cooperative food cloud*". Acceleration data processing, shelf life prediction, and real time supply chain re-planning are introduced as examples of on-site, in-system, and in-cloud information fusion respectively.

Finally, the implemented prototype system and results of field trials are presented. The feasibilities of the proposed design framework and solution have been confirmed. Limitations and future works are discussed too.

Appendix A

Table 6 Comparison between this work and others

Solutions	Field devices	Join design				Application scenarios				
		Value creation	Value assessment	Sensor portfolios	Information fusions	Produce	Store	Transport	Sell	Consume
Huang et al. 2006	RFID/PDA			x	x		x	x	x	
Jones 2006	RFID	x			x	x	x	x		
Kuck 2007	RFID	x		x		x	x	x	x	
Hsu et al. 2008	RFID				x	x	x	x	x	x
Abad et al. 2009	WSN			x			x	x	x	
Martínez-Sala et al. 2009	RFID	x			x		x	x	x	
Carullo et al. 2009	RFID/WSN			x			x	x	x	
Ruiz-Garcia et al. 2010	no	x			x	x	x	x	x	x
Sallabi et al. 2011	PDA	x			x	x				
Qi et al. 2011	RFID/WSN			x	x	x				
Rong et al. 2011	no				x	x	x	x	x	
Hulstijn et al. 2011	no	x		x		x	x	x	x	x
Lao et al. 2012	RFID	x		x	x	x	x	x	x	
This work	RFID/WSN	x	x	x	x	x	x	x	x	x

Appendix B

Table 7 Some of existing shelf life prediction models and applications

References	SQ1: quality index	SQ2: Q_e definition	SQ3: $Q'(t, E(t))$ modeling	SQ3: $E(t)$	SQ4: solving	Scope
Tijskens and Polderdijk 1996	General expression	Compare to known L in reference conditions	-Logistic growth kinetics -Temperature effect follows Arrhenius' law -Temporal-integration for dynamic temperature	-Temperature	-Analytical -Derive inverse function $Q^{-1}(\bullet)$	Fresh fruits & vegetables
Hertog et al. 1999	Percentage of affected strawberry	5 % of strawberry in one package spoiled	-Extent ion based on Tijskens et al.'s work (1996) -CO2 and O2 effect modeled as an additional coefficient mulitplying standard kinetics	-Temperature -CO2 -O2	Same as above	Strawberry
Dalgaard 1995	Cell concentration	30 mg-N trimethylamine (NTMA)/100 g	-Logistic growth kinetics (3- and 4-parameters) -Temperature effect follows Arrhenius' law -CO2 effect modeled as an additional coefficient mulitplied to the square root of standard kinetics	-Temperature - CO2	Same as above	Fresh fish
Dalgaard et al. 2002	Same as above	Same as above	-Seefood spoilage predictor software -Iterative approaches to calibrate	-Temperature	-Analytical -Computer aid	Seafood
Jedermann et al. 2011	Not available	Not available	-No new models -Applying existing models in wireless sensor system	-Temperature	- Numerical -Look up table	General fresh products
Oms-Oliu et al. 2008	-Color measured by CIELAB Space -Firmness measured by texture analyzer -Microbial counting	Not available	-Gompertz equation based growth kinetics -Static temperature of 4C - effect of CO2 and O2 concentrations and pressures are numerically compared without analytical models	-CO2 -O2 -Gas pressure	-Analytical - Numerical	Fresh-cut Melon
Tsironi et al. 2011	-CIELab Color measure	–Microbial counting to log 6.5 CFU/g at 4 °C	- exponential growth kinetics -Temperature effect follows Arrhenius' law	-Temperature	-Analytical -Aid by TTI label	Chilled seafood
Palazón et al. 2009	- non-sensory CIELab Color measure -And a sensory measure	50 % of panelists grade the sample as unacceptable (a cumulative hazard of 69.3)	–Linear and exponential growth kinetics -Temperature effect follows Arrhenius' law -Weibull hazard model to relate non-sensory and sensory evaluation	-Temperature	-Analytical	Beikost (baby food)

References

Abad, E., Palacio, F., Nuin, M., González de Zárate, A., Juarros, A., Gómez, J. M., & Marco, S. (2009). RFID smart tag for traceability and cold chain monitoring of foods: Demonstration in an intercontinental fresh fish logistic chain. *Journal of Food Engineering, 93*(4), 394–399.

Anastasi, G., Farruggia, O., Re, L. G., & Ortolani M. (2009). Monitoring high-quality wine production using wireless sensor networks. In Proceedings of the 42nd Hawaii international conference on system sciences, doi: 10.1109/HICSS.2009.313

Angeles, R. (2010). Moderated regression: Effects of IT infrastructure integration and supply chain process integration on the relationships between RFID adoption attributes and system deployment outcomes. In J. E. Quintela Varajão et al. (Eds.), CENTERIS 2010, Part II, CCIS 110, (pp. 406–415), 2010. Springer-Verlag: Berlin Heidelberg.

Atzori, L., Iera, A., & Morabito, G. (2010). The internet of things: a survey. *Computer Networks, 54*(15), 2787–2805.

Boddie, W., & Kun, L. (2008). Health care, public health, and the food and agriculture critical infrastructures. *IEEE Engineering in Medicine and Biology Magazine, 27*(6), 54–58.

Carullo, A., Corbellini, S., Parvis, M., & Vallan, A. (2009). A wireless sensor network for cold-chain monitoring. *IEEE Transactions on Instrumentation and Measurement, 58*(5), 1405–1411.

Chang, R. (1981). *Physical chemistry with applications to biological systems* (2nd ed.). New York: Macmillan Publishing Co, Inc.

Choe, Y. C., Park, J., Chung, M., & Moon, J. (2009). Effect of the food traceability system for building trust: price premium and buying behavior. *Information System Frontiers, 11*, 167–179.

Claire, S. (2011). Hartford encourages its food-industry clients to deploy RFID temperature tags. *RFID Journal.* Aug. 10, 2011.

Crisosto, C. H., Mitcham, B., & Cantwell, M. (2008). Optimum temperature conditions for producehandlers. *In Central Valley Postharvest Newsletter of University of California, 17*(3), 1–18.

Dalgaard, P. (1995). Modelling of microbial activity and prediction of shelf life for packed fresh fish. *International Journal of Food Microbiology, 26*(3), 305–317.

Dalgaard, P., Buch, P., & Silberg, S. (2002). Seafood spoilage predictor—development and distribution of a product specific application software. *International Journal of Food Microbiology, 73*(2–3), 343–349.

Duan, L., & Xu, L. (2012). Business intelligence for enterprise systems: a survey. *IEEE Transactions on Industrial Informatics*, published online, doi: 10.1109/TII.2012.2188804

European Commission Information Society (2008). Internet of things in 2020: a roadmap for the future. In reports of DG INFSO and EPoSS—05 September 2008.

European Commission Information Society (2009). Internet of things strategic research roadmap 2009. In reports of CERP-IoT cluster—15 September 2009.

EU (2002). Regulation (EC) No 178/2002 of the European parliament and of the council. *Official Journal of the European Communities. 1.2.2002*, L31/1–24.

Fellows, P. (2000). *Food processing technology: Principles and practice* (2nd ed.). Cambridge: Woodhead Publishing Limited.

German Insurance Association (2002–2011). Container Handbook. *Marine and loss prevention department of GDV*, www.containerhandbuch.de. Accessed Apr 23, 2012.

Goff-Pronost, M. L., & Sicotte, C. (2010). The added value of thorough economic evaluation of telemedicine networks. *The European Journal of Health Economics, 11*(1), 45–55.

Hertog, M. L. A. T. M., Boerrigter, H. A. M., van den Boogaard, G. J. P. M., Tijskens, L. M. M., & van SchaikOpen, A. C. R. (1999). Predicting keeping quality of strawberries (cv. 'Elsanta') packed under modified atmospheres: an integrated model approach. *Postharvest Biology and Technology, 15*(1), 1–12.

Hong, I.-H., Dang, J., Tsai, Y., Liu, C., Lee, W., Wang, M., & Chen, P. (2011). An RFID application in the food supply chain: a case study of convenience stores in Taiwan. *Journal of Food Engineering, 106*(2), 119–126.

Hsu, Y., Chen, A., & Wang, C. (2008). A RFID-enabled traceability system for the supply chain of live fish. In *Proceedings of IEEE International Conference on Automation and Logistics*, (pp. 81–86), doi: 10.1109/ICAL.2008.4636124

Huang, H., Chen, C., & Chen, T. (2006). Mobile diagnosis based on RFID for food safety. In *Proceedings of IEEE International Conference on Automation Science and Engineering* (pp. 357–362), doi: 10.1109/COASE.2006.326908.

Hulstijn, J., Christiaanse, R., Bharos, N., Schmid, F., Wijk, R., et al. (2011). Continuous Control monitoring-based regulation: A case in the meat processing industry. In: C. Salinesi and O. Pastor (Eds.) CAiSE 2011 workshops, LNBIP 83, (pp. 238–248). Berlin Heidelberg: Springer-Verlag.

ITU (2005). The internet of things-executive summary. International Telecommunication Union (ITU) Internet Report. http://www.itu.int/osg/spu/publications/internetofthings. Accessed Apr 23, 2012.

Jedermann, R., Palafox-Albarran, J., Jabarri, A., Lang, W., et al. (2011). Embedded intelligent objects in food logistics technical limits of local decision making. In M. Hülsmann (Ed.), *Autonomous cooperation and control in logistics*. Berlin: Springer. doi:10.1007/978-3-642-19469-6_16.

Jones, P. (2006). Networked RFID for use in the food chain. In *Proceedings of IEEE Conference on Emerging Technologies and Factory Automation* (pp. 1119–1124), doi: 10.1109/ETFA.2006.355252

José, á. M., Berrone, P., Husillos, F. J., & Lado, N. (2007). Reverse logistics, stakeholders' influence, organizational slack, and managers' posture. *Journal of Business Research, 60*(5), 463–473.

Kim, Y., Evans, R. G., & Iversen, W. M. (2008). Remote sensing and control of an irrigation system using a distributed wireless sensor network. *IEEE Transactions on Instrumentation and Measurement, 57*(7), 1379–1387.

Kuck, M. (2007). The chill-on project: Novel technologies for a safe and transparent food supply. http://www.chill-on.com. Accessed Apr 23, 2012.

Lao, G., & Wang, Qi. (2008). A circulation management model for safer food supply based on RFID. In *Proceedings of 4th International Conference on Wireless Communications, Networking and Mobile Computing* (pp. 1–4).

Lao, S. I., Choy, K. L., Ho, G. T. S., Tsim, Y. C., Poon, T. C., & Cheng, C. K. (2012). A real-time food safety management system for receiving operations in distribution centers. *Expert Systems with Applications, 39*(3), 2532–2548.

Lea-Cox, J. D., Kantor, G., Anhalt, J., Ristvey, A., & Ross, D. S. A. (2007). Wireless sensor network for the nursery and greenhouse industry. In *Proceedings of in southern nursery association research conference*, Vol. 52.

Lee, W. S., Alchanatis, V., Yang, C., Hirafuji, M., Moshou, D., & Li, C. (2010). Sensing technologies for precision specialty crop production. *Computers and Electronics in Agriculture, 74*(1), 2–33.

Li, L. (2007). *Supply chain management: Concepts, techniques, and practices—enhancing value through collaboration*. World Scientific Publishing.

Li, L. (2011). Assessing the relational benefits of logistics services perceived by manufacturers in supply chain. *International Journal of Production Economics, 132*, 58–67.

Li, L., & Warfield, J. (2011). Guest editorial: perspectives on quality coordination and assurance in global supply chains. *International Journal of Production Research, 49*(1), 1–4.

Li, S., Xu, L., Wang, X., & Wang, J. (2012). Integration of hybrid wireless networks in cloud services oriented enterprise information systems. *Enterprise Information Systems, 6*(2), 165–187.

Liu, R., & Kumar, A. (2011). Leveraging information sharing to configure supply chains. *Information System Front, 13*, 139–151.

López, T. S., Ranasinghe, D. C., Patkai, B., & McFarlane, D. (2011). Taxonomy, technology and applications of smart objects. *Information Systems Frontiers, 13*(2), 281–300.

Man, C. M. D., & Jones, A. A. (2000). *Shelf-life evaluation of foods* (2nd ed.). New York: Aspen.

Martinez-Romero, D., Serrano, M., Carbonell, A., Castillo, S., Riquelme, F., & Valero, D. (2004). Mechanical damage during fruit post-harvest handling: Technical and physiological implications. In R. Dris & S. M. Jain (Eds.), *Production practices and quality assessment of food crops, vol. 3, "Quality handling and evaluation"* (pp. 233–252). Netherlands: Kluwer.

Martínez-Sala, A. S., Egea-López, E., Garcia-Sanchez, F., & García-Haro, J. (2009). Tracking of Returnable Packaging and Transport Units with active RFID in the grocery supply chain. *Computers in Industry, 60*(3), 161–171.

McWilliams, G. (2006). Wal-Mart's radio-tracked inventory hits static. *Wall Street Journal*. February 15, 2006, page B1.

Oms-Oliu, G., Martínez, R. R. M., Soliva-Fortuny, R., & Martín-Belloso, O. (2008). Effect of superatmospheric and low oxygen modified atmospheres on shelf-life extension of fresh-cut melon. *Food Control, 19*(2), 191–199.

Pang, Z., Chen, J., Sarmiento, M. D., Zhang, Z., Gao, J., Chen, Q., & Zheng, L. (2009). Mobile and wide area deployable sensor system for networked services. In *Proceedings of IEEE sensors conference* (pp. 1396–1399). doi: 10.1109/ICSENS.2009.5398428.

Pang, Z., Chen, J., Zhang, Z., Chen, Q., & Zheng, L. (2010). Global fresh food tracking service enabled by wide area wireless sensor network. In *Proceedings of IEEE sensors applications symposium (SAS2010)*, (pp. 6–9), doi: 10.1109/SAS.2010.5439425.

Pang, Z., Chen, Q., & Zheng, L. (2012). Scenario-based design of wireless sensor system for food chain visibility and safety. *Advances in Computer, Communication, Control and Automation. Lecture Notes in Electrical Engineering, 121*, 541–548. doi:10.1007/978-3-642-25541-0_69.

Palazón, M. A., Pérez-Conesa, D., Abellán, P., Ros, G., Romero, F., & Vidal, M. L. (2009). Determination of shelf-life of homogenized apple-based beikost storage at different temperatures using Weibull hazard model. *LWT- Food Science and Technology, 42*(1), 319–326. doi:10.1016/j.lwt.2008.03.011.

Qi, L., Zhang, J., Xu, M., Fu, Z., Chen, W., & Zhang, X. (2011). Developing WSN-based traceability system for recirculation aquaculture. *Mathematical and Computer Modeling, 53*(11–12), 2162–2172.

Rong, A., Akkerman, R., & Grunow, M. (2011). An optimization approach for managing fresh food quality throughout the supply chain. *International Journal of Production Economics, 131*, 421–429.

Ruiz-Garcia, L., & Lunadei, L. (2011). The role of RFID in agriculture: applications, limitations and challenges. *Computers and Electronics in Agriculture, 79*(1), 42–50.

Ruiz-Garcia, L., Lunadei, L., Barreiro, P., & Robla, J. I. (2009). A review of wireless sensor technologies and applications in agriculture and food industry: state of the art and current trends. *Sensor, 9*(6), 4728–4750. doi:10.3390/s90604728.

Ruiz-Garcia, L., Steinberger, G., & Rothmund, M. (2010). A model and prototype implementation for tracking and tracing agricultural batch products along the food chain. *Food Control, 21*(2), 112–121.

Sallabi, F., Fadel, M., Hussein, A., Jaffar, A., & Khatib, H. E. (2011). Design and implementation of an electronic mobile poultry production documentation system. *Computers and Electronics in Agriculture, 76*(1), 28–37.

Sarac, A., Absi, N., & Dauzère-Pérès, S. (2010). A literature review on the impact of RFID technologies on supply chain management. *International Journal of Production Economics, 128*(1), 77–95.

Sheng, Q., Zeadally, S., Luo, Z., Chung, J., & Maamar, Z. (2010). Ubiquitous RFID: where are we? *Information Systems Frontiers, 12*(5), 485–490.

Shin, T.-H., Chin, S., Yoonc, S.-W., & Kwonb, S.-W. (2011). A service-oriented integrated information framework for RFID/WSN-based intelligent construction supply chain management. *Automation in Construction, 20*(6), 706–715.

Sinderen, M., & Almeida, J. P. A. (2011). Empowering enterprises through next-generation enterprise computing. *Enterprise Information Systems, 5*(1), 1–8.

Strauss, C., Stummer, C., Bauer, C., & Trieb, A. (2009). A networked ubiquitous computing environment for damage prevention: a decision support framework for the insurance sector. In *Proceedings of International Conference on Parallel Processing Workshops* (pp. 276–281), doi: 10.1109/ICPPW.2009.79.

Tajima, M. (2007). Strategic value of RFID in supply chain management. *Journal of Purchasing & Supply Management, 13*, 261–273.

Tijskens, L. M. M., & Polderdijk, J. J. (1996). A generic model for keeping quality of vegetable produce during storage and distribution. *Agricultural Systems, 51*(4), 431–452.

Tsironi, T., Gogou, E., Velliou, E., & Taoukis, P. S. (2008). Application and validation of the TTI based chill chain management system SMAS (Safety Monitoring and Assurance System) on shelf life optimization of vacuum packed chilled tuna. *International Journal of Food Microbiology, 128*(1), 108–115.

Tsironi, T., Stamatiou, A., Giannoglou, M., Velliou, E., & Taoukis, P. S. (2011). Predictive modelling and selection of time temperature integrators for monitoring the shelf life of modified atmosphere packed gilthead seabream fillets. *LWT-Food Science and Technology, 44*(4), 1156–1163. doi:10.1016/j.lwt.2010.10.016.

Ugazio, E., & Pigni, F. (2010). Measuring RFID benefits in the supply chain. In A. D'Atri & D. Saccà (Eds.), *Information systems: People, organizations, institutions, and technologies, Part 8* (pp. 469–476). Berlin: Springer.

Victoria de-la-Fuente, M., Ros, L. (2010). What to Do with Rejected Loads in the Agri-food Chain. In J.E. Quintela Varajão et al. (Eds.): CENTERIS 2010, Part I, CCIS 109, pp. 251–260, 2010. Berlin Heidelberg, Springer-Verlag.

Visich, J. K., Reyes, P. M., & Li, S. (2011). Is RFID dead? Definitely not! *DC Velocity Technology Review*. June 27, 2011.

Voisard, A., & Ziekow, H. (2010). Modeling trade-offs in the design of sensor-based event processing infrastructures. *Information Systems Frontiers, 14*(2), 317–330.

Wamba, S. F., & Chatfield, A. T. (2010). The impact of RFID technology on warehouse process innovation: a pilot project in the TPL industry. *Information Systems Frontiers, 13*(5), 693–706.

Xu, L. (2011a). Enterprise systems: state-of-the-art and future trends. *IEEE Transactions on Industrial Informatics, 7*(4), 630–640.

Xu, L. (2011b). Information architecture for supply chain quality management. *International Journal of Production Research, 49*(1), 183–198.

Yoo, S., Kim, J., Kim, T., Ahn, S., Sung, J., & Kim, D. (2007). A2S: automated agriculture system based on WSN. *IEEE*

International Symposium on Consumer Electronics. doi:10.1109/ISCE.2007.4382216.

Zhang, M., & Li, P. (2012). RFID application strategy in agri-food supply chain based on safety and benefit analysis. *Physics Procedia, 25*, 636–642.

Zhang, W. (2010). Market Research for RFID Real-time Cold-chain Monitoring System. *Master Thesis of Royal Institute of Technology*, No.TRITA-ICT-EX-2010:296

Mr. Zhibo Pang is a research scientist at ABB Corporate Research, Sweden, and a Ph.D. candidate at Royal Institute of Technology (KTH), Stockholm, Sweden. He received his B.Eng. degree in electronics engineering from Zhejiang University in 2002, and MBA in Innovation and Growth from University of Turku in 2012. Before joined KTH and ABB, he worked as technical manager in semiconductor industry, designing base-band and application processors for consumer smart devices. His current research interests include the Internet-of-Things, radio frequency identification, wireless sensor network, industrial communication, real time embedded system, enterprise information systems, system-on-chip, and network-on-chip. He has 14 patents in these areas. He is also working on the business-technology joint research such as business model design, value chain formulation, strategy, and entrepreneurship/intrapreneurship. He was awarded the National Great Invention Award by the Ministry of Information Industry of China in 2005, and won the First Place Prize of the RFID Nordic EXPO in 2008.

Dr. Qiang Chen is a senior research fellow at Department of Electronic System and VINN Excellence Center iPack, School of Information and Communication Technology (ICT), the Royal Institute of Technology (KTH), Stockholm, Sweden. He received his Ph.D. degree in microelectronics from Linköping University, Linköping, Sweden in 1993. He worked from 1994 to 2002 at Ericsson and became Ericsson Corporate Expert in RF microelectronics in 2001. He joined Infineon Technology Sweden in 2003 as a Principal. Since 2008 he was with KTH as a senior research fellow and project leader at Department of Electronic System. His experiences and research interests include RF microelectronics, wireless sensor network and sensor technology, and printed electronics. He has published more than 50 international reviewed scientific papers and several book chapters.

Dr. Weili Han is an associate professor at Fudan University. His research interests are mainly in the fields of Access Control, Digital Identity Management and Service Oriented Architecture. He is now the members of the ACM, SIGSAC and CCF. He received his PhD of Computer Science and Technology at Zhejiang University in 2003. Then, he joined the faculty of Software School at Fudan University. From 2008 to 2009, he visited Purdue University as a visiting professor funded by China Scholarship Council and Purdue.

Dr. Li-Rong Zheng received his Ph. D. degree in electronic system design from the Royal Institute of Technology (KTH), Stockholm, Sweden in 2001. Since then, he was with KTH as a research fellow and project leader in Laboratory of Electronics and Computer Systems. He became an associate professor in electronics system design in 2003 and a full professor in media electronics at KTH in 2006. He is the founder and director of iPack VINN Excellence Center, and Senior Specialist of Ericsson Networks in Stockholm, Sweden. He is a guest professor of the state key laboratory of ASICs and Systems at Fudan University in China since 2008, and a distinguished professor of Fudan University since 2010. His research experience and interest includes electronic circuits and systems for ambient intelligence and media applications, wireless sensing and identification, and signal integrity issues in electronic systems. He has authored and co-authored over 300 international reviewed publications, covering areas from electronic devices and thin film technologies, VLSI circuit and system design, to electronics systems and wireless sensors.