

Towards Edge Computing Based Monitoring for Smart Ports

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Abstract. The development of smart ports requires the use of modern innovative digital solutions based on the latest advances in information and communication technologies. The Internet of Things opens the way for the creation of efficient technologies for smart ports. Smart sensors are a key element of the port's digital infrastructure. For example, wireless sensor networks that detect or predict pipeline leaks and inform port operators can prevent catastrophic environmental disaster and huge economic losses. The paradigm of Edge computing, where data is processed close to its source, alleviates the problem of transferring and storing huge amounts of sensing data. Smart sensors can analyze data, make decisions and transmit results to port operators in a compact form. Thus, the problem is to optimize the transmission of the computed solution, taking into account the trade-off between cost and reliability. In this paper, we focus on this issue.

Keywords: Wireless sensor networks · Edge computing · Infrastructure monitoring

1 Introduction

The development of smart ports requires the use of modern innovative digital solutions based on the latest advances in information and communication technologies. Lack of accurate and timely information about the health of the port infrastructure results in many errors, severe delays and redundant labor-intensive work. Further, a decrease in the capacity of an individual transport hub can drastically affect the global supply chains. Seaports handle 80% of the world trade [1]. In the port, the interests of the transport, industrial and civil sectors are closely intertwined, giving rise to multifaceted problems of ensuring the reliability, productivity and profitability of logistics services. The Internet of Things (IoT) opens the way for the creation of technologies for smart ports that can effectively solve the following tasks: maintain an ever-growing foreign trade turnover and service associated traffic flows, reduce potentially harmful impacts on the environment and public health, prevent anthropogenic disasters, increase resilience to natural disasters, and support the efficient resource consumption [2].

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Smart sensors are a key element of the port's digital infrastructure. These sensors are mounted on container yards, cranes, roads, pipelines and can transmit real-time data about working conditions of docks and other infrastructure. Smart sensors can reduce the need for regular inspections and provide data that helps owners plan preventive maintenance more effectively. The cost of many sensor systems for structural health monitoring can be included in the cost of the structures themselves. This can lead to a quick return on investment in countries with high labor costs. The handling equipment of any transport hub must operate at maximum efficiency and be properly maintained. A wireless sensor networks can ensure that connected handling equipment is servicing the increasing volume of cargo shipments in real time. Smart sensors installed in container terminals collect information about the location of cargo and equipment, the status of operations and energy consumption. The information system analyzes information in real time and transmits it to terminal personnel to identify bottlenecks and initiate appropriate actions. In this way, operating costs can be significantly reduced by reducing equipment downtime and minimizing energy consumption.

Seaports must meet certain safety standards. The smart sensors can be used for motion-based intrusion detection and pattern recognition, and then the sensors, using network technology, alert security personnel of potential threats. Sensor networks help address security concerns in ports by providing safe operating procedures. For example, sensor networks can alert vehicle drivers to stay within the track. Similar systems can maintain the correct alignment of the cranes during loading and unloading etc.

An important component of the seaport infrastructure is pipelines for the transportation of liquid cargo, including crude oil, oil products, chemicals and industrial gases. For example, the port of Rotterdam has an extensive network of more than 1,500 km of pipelines [3]. Also, extensive pipeline networks connect ports and industrial clusters. Intelligent sensor networks that detect or predict pipeline leaks can prevent catastrophic environmental disaster and huge economic losses [4].

In recent articles, researchers have noted the following topical challenges that wireless sensor networks face in smart ports [5]. Network nodes share and retransmit huge amounts of data and information in real time. Therefore, the problem of energy consumption requires attention. Next, the port environment is unfavorable for wireless communication. The signal can be shielded, reflected, and scattered. This results in data packets corruption and degraded network performance.

The paradigm of Edge computing, where data is processed close to its source, alleviates the problem of transferring and storing huge amounts of data. Smart sensors can analyze data, make decisions and transmit results to port operators in a compact form. Thus, the problem is to optimize the transmission of the computed solution, taking into account the trade-off between cost and reliability. In this paper, we focus on this issue.

The remainder of this paper is organized as follows. Section 2 provides related works. Section 3 formulates a system model, problem statements and provides the corresponding mathematical results. The performance analysis of these results is provided in Sect. 4. Conclusions are drawn in Sect. 5.

2 Related Works

There is a lack of publications regarding smart port monitoring systems. Usually, to improve the efficiency of the port operations, investigators develop simulation or analytical models using some averaged historical data or not using data at all [6–8].

In [9], the authors noted that an intelligent information system can improve the visibility, reliability and safety of a marine terminal, and cited the example of the port of Marseille, where the doublet of Neptune and Ci5 improved the quality of service for the flow of goods. However, as also noted, an intelligent information system required constant exchange of data and information between ports. Smart sensors must collect and transmit huge amounts of data such as geolocation, sea depth, wind speed, humidity, temperature, vibration, pressure, shock, etc.

The use of intelligent monitoring systems in the port shows great potential. Indeed, one of the most important and serious problems of modern cities is air pollution. Experts from the World Health Organization and the United Nations are expressing serious concern about this. A promising way to address this challenge is to use networks of smart sensors [10]. The maritime ports make a significant contribution to the pollution of the urban atmosphere. For example, the port's contribution to Shanghai's air pollution is about 30% only for the major air pollutants (SO_2, NO_x and $PM_{2.5}$) and the Port of Hamburg produces about 28% of the NO_x emissions of the entire city [11]. In addition, it is noted that quantitative data on emissions from ports can only give an approximate picture of reality. The assessment of the corresponding contribution to pollution can be based on indirect information such as data from a similar port or subjective opinions of experts. Also, due to imperfect equipment, the data collected may be incomplete or inaccurate. There are precedents for port terminal emissions studies based on confidential and inaccurate data [12]. Next, aggregated anonymized data collected in a traditional way can be useful for obtaining environmental certifications. However, detailed data are needed to adequately control emissions and make effective decisions to reduce air pollution. Intelligent monitoring systems allow emissions to be assigned to specific sources or categories of emissions, such as ocean vessels, vehicles, handling equipment etc.

Currently, various political and social groups are actively discussing the danger of greenhouse gases, taking measures to reduce emissions of air pollutants, and lobbying for appropriate decisions at the intergovernmental level. This problem is in the focus of attention of the media and the public. There is growing interest in air quality issues and increased public support for action to reduce emissions. Given the intensity of maritime trade, we can expect an increasing demand for comprehensive and high quality air emission inventory tools. As a consequence, it can be predicted that port organizations will actively develop, implement and improve air emission inventory processes [13].

Let us remark that monitoring is also needed for other emissions such as sewage, noise emissions etc. Edge computing based monitoring for smart ports enables efficient monitoring of different emissions, detection of pollution sources and the introduction of environmentally friendly technologies such as vacuum mooring systems to reduce engine run time. It also opens up opportunities for optimizing the port operation in order to effectively improve the environmental situation. The lack of research on information systems for smart ports comes as a particular surprise [14].

The information systems for smart ports have been briefly described in [15]. In the recent survey [5] author claim that modern information systems for smart ports have to be deployed to manage, monitor, and store massive amounts of various data. And hence, application of Edge computing for the smart port tasks is an attractive open research challenge.

3 Models

Assume, smart sensors treat data (e.g. using a lightweight machine learning algorithm [16]) and get decision, which has to be delivered to port operators through a binary wireless communication channel. The sensor report is a message of N bits. Let the probability of an error of a single bit is p. If a redundant noise-correcting code is used, then the code is capable of correcting up to k errors. For example, if we use a double error-correcting Hamming code then $k = 2$. Therefore, the link transmission of a message is successful if

$$n_e \leq k$$

where n_e is the number of errors in the message. The transmission of bits is assumed to be independent. The designation h is used for the distance between the sensor and the sink in the term of hops (i.e. h hops). The topology of subnetwork sensor-sink is a simple chain.

Let us calculate the probability of successful message transmission. We use the property of Bernoulli trials, i.e.

$$F(x) = \begin{cases} 0, & x < 0 \\ 1 - p, & 0 \leq x < 1 \\ 1, & x \geq 1 \end{cases}$$

where $F(x)$ is CDF of the random variable as follows: the number of errors in a single bit (0 or 1). Let us consider an elementary event when there are exactly j errors in a message containing N bits. It follows from the properties of independent random variables that the probability of this event is

$$p^j (1 - p)^{N-j}$$

Noting that the number of ways of taking j bits from N possibilities is described by the corresponding binomial coefficient C_N^j,

$$C_N^j = \frac{N!}{j!(N - j)!}$$

Thus, we have got the binomial distribution

$$P(n_e = j) = \frac{N!}{j!(N - j)!} p^j (1 - p)^{N-j}, \quad j \in \mathbb{N}_{[0;N]}$$

and next

$$P(n_e \leq k) = \sum_{j=0}^{k} C_N^j p^j (1-p)^{N-j}$$

This is the probability of one link successful transmission. Now, there are two possible situations:

- An intermedia node transmits the message and only a sink restore the message.
- The message is corrected (if it is necessary) in each intermedia node.

Without loss of generality, we pass the case of message recovery after an even number of errors in the same bit. In the first case 1 bit of the message is correctly transmitted with the probability p^h. Therefore, the probability of final success in this case is as follows:

$$P_1 = \sum_{j=0}^{k} C_N^j q^j (1-q)^{N-j}$$

where

$$q = 1 - (1-p)^h$$

In the second case

$$P_2 = \left(\sum_{j=0}^{k} C_N^j p^j (1-p)^{N-j} \right)^h$$

In the case of heterogeneous error probability these formulas are modified as follows

$$P_1 = \sum_{j=0}^{k} C_N^j \left(1 - \prod_{i=1}^{h} (1-p_i) \right)^j \left(\prod_{i=1}^{h} (1-p_i) \right)^{N-j}$$

and

$$P_2 = \prod_{i=1}^{h} \sum_{j=0}^{k} C_N^j p_i^j (1-p_i)^{N-j}$$

where $p_i,\ i \in [1, h]$ is the 1-bit error probability in the i-th link.

To improve packet delivering reliability multiple stock can be used [17]. It is reasonable to assume that the sinks are located at the boundaries of the chain formed by the sensors, and the transmission is carried out in both directions. Cognitive radio technologies can be used to prevent interference and spectrum cost problems in highly dynamic environments [18–20]. The formulas for reliable transmission become as follows:

$$P_1 = \sum_{j=0}^{k} C_N^j (1-(1-p)^h)^j (1-p)^{h(N-j)}$$

$$+\sum_{j=0}^{k} C_N^j \left(1-(1-p)^{L-h}\right)^j (1-p)^{(L-h)(N-j)}$$
$$-\sum_{j=0}^{k} C_N^j \left(1-(1-p)^{h}\right)^j (1-p)^{h(N-j)}$$
$$*\sum_{j=0}^{k} C_N^j \left(1-(1-p)^{L-h}\right)^j (1-p)^{(L-h)(N-j)}$$

and

$$P_2 = \left(\sum_{j=0}^{k} C_N^j p^j (1-p)^{N-j}\right)^h + \left(\sum_{j=0}^{k} C_N^j p^j (1-p)^{N-j}\right)^{L-h} - \left(\sum_{j=0}^{k} C_N^j p^j (1-p)^{N-j}\right)^L$$

where L is the length of the chain. By combining the options of recovering messages in intermediate nodes and one/two sinks, we get four strategies for delivering the resulting message. The formulas can be easily generalized for star topologies.

4 Performance Analysis

It is clear that the second approach to transmit the message with decision is more reliable than the first approach, i.e.

$$P_1 < P_2 \ \forall N, k, h$$

However, the price for this is the energy consumption for packet recovering relay nodes.

It needs to remark, that in the case of single sink and $h = 1$ the message is recovering once, so we cannot to say about the choice of strategies.

For the case of two sinks, the lowest reliability corresponds to a node equal to the distance from both sinks. If L is odd, then there are two such sensors. The value of this reliability is as follows:

$$P_{min} = 2\left(\sum_{j=0}^{k} C_N^j p^j (1-p)^{N-j}\right)^{L/2} - \left(\sum_{j=0}^{k} C_N^j p^j (1-p)^{N-j}\right)^L$$

Increasing the packet length, we improve the transmission reliability. However, starting from a certain value p, this length becomes unimportant. This proposition is demonstrated in Figs. 1, 2 and 3.

Here, the message length ranges from 5 to 21 bits, and the probability of error in one bit ranges from 0.01 to 0.5. The threshold for the number of errors is assumed to be as follows:

$$k = \left\lfloor \frac{N}{2} \right\rfloor$$

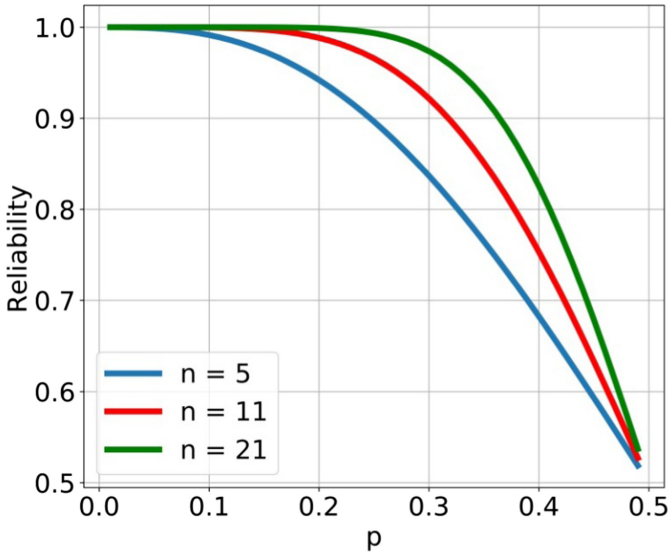

Fig. 1. The effect of one-bit error probability, $h = 1$.

There is a single sink. The option of message recovering in intermedia nodes has been applied. If the probability of an error in one bit is large enough ($p > 0.5$), the reliability is practically independent of the message length. This situation is typical for jamming attacks. Also, if p is small enough ($p < 0.1$) then it is reasonable to use short messages and thus save the energy of network nodes.

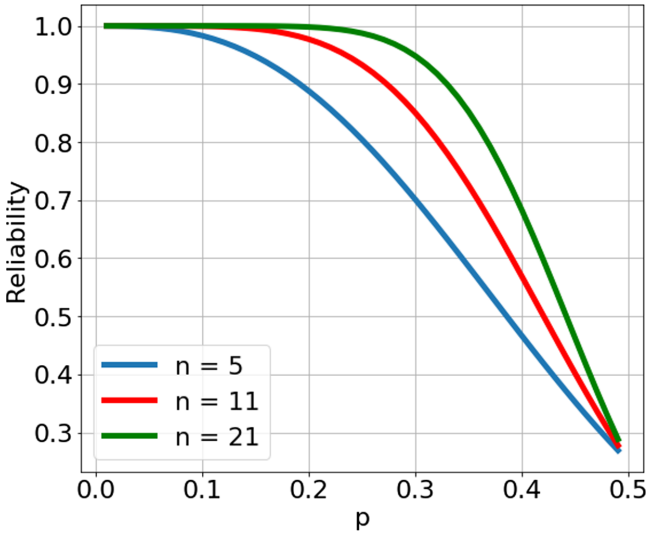

Fig. 2. The effect of one-bit error probability, $h = 2$.

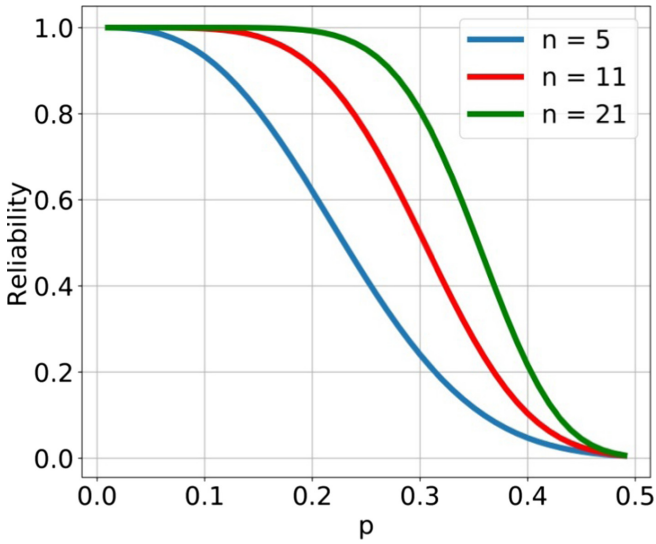

Fig. 3. The effect of one-bit error probability, $h = 8$.

The reliability drastically decreases with increasing the sensor-to-sink distance.

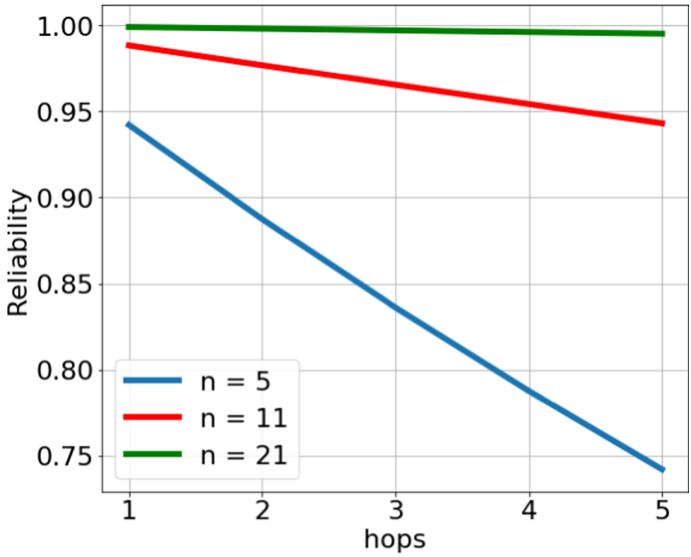

Fig. 4. Number of hops vs packet length, $p = 0.2$.

Also, it needs to remark that the packet size prevails over sensor-to-sink distance while maintaining transmission reliability. It is shown in Fig. 4. We can achieve a significant improvement in delivery reliability by increasing the message length.

5 Conclusion

While the benefits of smart systems for cost-effectiveness, security and environmental safety of ports have been discussed in the literature, the use of the Edge computing concept in this area remains an open issue. In this work, we propose to partially fill the noted gap. We have proposed mathematical models for a scenario when a smart sensor independently processes data and generates an output. The task is reduced to reliable delivery of the result to the addressee. We looked at several delivery scenarios and analyzed the parameters that affect delivery reliability.

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