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An AI-IoT Inventory Management Approach to Optimize Cold Storage Replenishment and Energy Cost

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ABSTRACT

To support retail sustainability, retailers must also focus on energy efficiency. Cold storage is a major factor in the retail sector's rising energy use. Improving cold storage saves energy. Poorly filled or used cold storage wastes energy and increases costs. This situation pertains to retail inventory management. Therefore, retail inventory management is crucial. This study aims to develop an Artificial Intelligence (AI)-and IoT (Internet of Things)-based inventory management model to improve cold storage replenishment efficiency while considering energy costs. The suggested solution includes an inventory management model and application that alerts retail managers to quickly replace cold storage items and keep inventory levels steady. The suggested inventory management approach comprises two phases: development and execution. The development phase begins with data collection, using sensors and a microcontroller to monitor cold storage. The suggested framework incorporates the following data: 1) cold storage door opening and closing times, 2) electrical energy consumption, 3) cold storage temperature, 4) product weight, and 5) product photos. The Convolutional Neural Network (CNN) is applied to categorize visual input for generating refill alerts. Experimental results suggest that the proposed strategy effectively reduces total energy costs per unit by 18.1% and total inventory costs by 6.9% when compared to the typical periodic review inventory management model.

Keywords: *artificial intelligence (AI), cold storage, energy efficiency, internet of things (IoT), inventory management, retail sustainability*

1. INTRODUCTION

Sustainability refers to concepts or actions designed to achieve success for both present and future generations through the integration of economic, environmental, and social strategies (Vadakkepatt *et al*., 2021). The topic of sustainability warrants current discussion. The United Nations supports this initiative by introducing sustainable development goals (SDGs) aimed at fostering favorable conditions for humans and the planet and achieving prosperity (United Nations, 2015). Sustainability is the collective responsibility, including the retail industry (Erez, 2019; Widlitz, 2020). Retail is a form of industry that aims to connect manufacturers with end users. The retail industrial sector ranks among the largest economic sectors, with retail growth estimated to reach 4.9% in 2024 (Oberlo, 2024). Retail is also characterized by its labor-intensive industry and requires strong customer interaction to ensure a positive shopping experience (Jones *et al*., 2005). Apart from its economic contribution, retail also faces challenges in dealing with several sustainability issues (Jones *et al*., 2005). Retail consumers increasingly consider sustainability factors in their shopping decisions (First Insight, Inc., 2021); thus, emphasizing sustainability in the retail sector is essential.

Two important aspects of sustainability in retail are transportation and environmentally friendly store operations (Yang *et al*., 2017). The two aspects are closely related to energy issues, which are significant factors in sustainability and economics (Rogner & Popescu, 2001). The retail sector has relatively significant energy consumption compared to other industrial sectors, with figures ranging from 500 to 1000 kWh/m²/year (British Retail Consortium, 2016; Schönberger *et al*., 2013). The use of cold storage is a contributing factor. Cold storage accounts for approximately 45% of total retail energy consumption in the retail sector (Energy Star, 2008). User habits significantly impact cold storage energy consumption, particularly the frequency of door openings and the volume of products stored (Geppert & Stamminger, 2010; Saidur *et al*., 2002). It is often found that cold storage is not fully filled or empty.

That condition will, of course, have an impact on the possibility of lost sales, waste of electrical energy, and increased energy costs for each product stored. Cold storage must be kept full so that cooling can run more efficiently, reduce energy consumption, and reduce energy costs per product (Marchi *et al*., 2020). Energy efficiency efforts are an important step before exploring new energy sources or increasing energy production (International Energy Agency, 2022). According to Pramudika *et al*. (2023), there is a need to develop practices that support sustainable retail, especially in the energy sector, which is caused by using cold storage in retail operations.

Because monitoring the use of energy storage in the cold storage is difficult to perform manually, therefore the use of sensors is needed. Hence, the concept of Internet of Things (IoT) which are the most important contributors to the current industrial revolution (Rahman *et al*., 2023) can be applied in this situation.

In the past, a concept called a smart refrigerator or smart storage has emerged, where this tool has an additional function apart from being a place to store goods at cold temperatures, and this additional function shows smart aspects in storage operations, for example, sending information about storage conditions (Gürüler, 2015; Edward *et al*., 2017; Zhongmin & Yanan, 2018), automatically placing online orders to refill the storage (Khan *et al*., 2019), predicting the quality of items in the storage (Rajeswari *et al*., 2022), and reducing food waste (Srinivasan, 2022). Enablers that can be used to create a smart refrigerator are technological developments in terms of sensors, controllers, and transmission (Hachani *et al*., 2016; Khan *et al*., 2019). A similar idea can, of course, be used in energy efficiency efforts for cold storage.

As mentioned in the previous paragraph, the inefficient use of energy in cold storage is partly due to the quantity of products stored there. Inventory management, which includes determining inventory policies, closely relates to this. The use of IoT in cold storage enables automatic monitoring of cold storage conditions. Therefore, the integration of IoT and data processing using machine learning or artificial intelligence (AI) to be integrated with inventory management, including in the retail sector, is very necessary. Research on inventory management and AI application has been found related to the demand or sales forecasting process (Rekha & Vijaykumar, 2019; Benhamida *et al*., 2021; Wang *et al*., 2023). For some uses, AI can also be used to sort inventory (Li *et al*., 2023; Qaffas *et al*., 2023) and in inventory monitoring systems to cut down on mistakes made by people using paper or traditional systems (Agarwal *et al*., 2020; Milella *et al*., 2020; Sikkandhar *et al*., 2023) and not just for forecasting.

Based on the explanation above, the main challenge that can be identified is how to address the issue of sustainability in the retail industry, namely through energy efficiency in retail because this industry consumes a large amount of energy. The big energy use comes from cold storage and inventory management, and no previous research has looked at this issue in the context of cold storage and inventory management. This study proposes a framework for how to combine IoT technology, AI especially Convolution Neural Network (CNN), and inventory management in retail to help make decisions about when to restock cold storage by taking energy costs into account as part of efforts to support environmentally or energy-friendly retail practices. This model allows for automatic inventory monitoring in cold storage. In addition, how much product should be replenished in cold storage to minimize energy usage and energy costs per unit of product stored can be achieved using the proposed framework.

2. LITERATURE REVIEW

2.1 Sustainable Retail Related to Energy Issues

Currently, retailers have implemented various green practices, such as waste management, energy and water efficiency, biodiversity protection, transportation efficiency, and compliance with existing standards or certifications (Grosu, 2023). The Paris Agreement is the beginning of implementing a decarbonization strategy in retail with the aim of managing climate change issues, such as setting energy goals, investing in efficient supply chains, environmentally friendly retail operations, and building design that focuses on energy efficiency (Ferreira *et al*., 2019). Several studies discuss the development of assessment and evaluation methods in retail buildings, such as Gulliford *et al*. (2022), who assessed emissions and cost performance in retail; Gabriel Filho *et al*. (2023), who applied the PROCEL energy evaluation method to an agribusiness retail; and Ferreira *et al*. (2019), who established the Building Sustainability Assessment (BSA) methodology for retail structures. Research on energy has been conducted by Severinsen and Myrland (2022), Barchi *et al*. (2019), Saabit *et al*. (2021), Syed & Hachem (2019), and Syed & Hachem-Vermette (2023), focusing on energy efficiency in retail buildings. Furthermore, research related to retail buildings is related to the use of renewable energy sources also conducted by several researchers, such as Accurso *et al*. (2021), Acha *et al*. (2020), and Ayoub *et al*. (2020). Besides energy issues in retail buildings, previous research also discussed energy issues in retail transportation activity. This activity is an activity to move goods from one place to another place using transportation mode and will certainly have an impact on the environment, such as carbon emissions. Bas & Ozkok (2023) developed the Linear Fractional Vehicle Routing Problem (LFVRP) method, which considers multiple objectives, namely load and costs, to minimize fuel consumption while maintaining maximum load. Heshmati *et al*. (2019) and Muñoz-Villamizar *et al*. (2022) evaluated delivery times with the aim of increasing efficiency, saving costs, and reducing carbon emissions. Recent research conducted by Winkler *et al*. (2022) related to the decarbonization efforts in transportation activities using new and more environmentally friendly energy sources. Previous research also highlights the issue of energy resulting from the use of cooling systems. Research is being carried out to replace cooling systems with environmentally friendly refrigerants (Expósito-Carrillo *et al*., 2021; Hart *et al*., 2020). Other research also discusses proposing a more efficient cooling engine mechanism (Efstratiadi *et al*., 2019; Sengupta & Dasgupta, 2023). There is also research that seeks to reuse the heat energy produced by cooling machines to heat rooms and replace conventional space heating systems (Maouris *et al*., 2020).

Based on the description above regarding research in the field of sustainable retail related to energy issues, a lot of research has been carried out, especially with respect to 1) energy related to retail buildings, 2) energy related to retail transportation activities, and 3) energy related to cooling storage technology. Meanwhile, previous research with respect to energy related to retail operational activities, including inventory management decisions and replenishment of goods in cold storage, which has a relatively large contribution to energy consumption, has never been carried out by previous researchers.

2.2 Smart Cold Storage (Smart Refrigerator)

Smart cold storage, or smart refrigerators, provide users with various additional functions that do not exist in the conventional ones, which only keep inventories at low temperatures. Some functions that have ever been proposed, such as informing the amount of items in the storage (Gürüler, 2015), informing the electrical power status of the storage (Gürüler, 2015), providing real-time information to users about the condition of storage (Zhongmin & Yanan, 2018), sending online crucial notifications regarding storage, i.e., expired items and storage temperature rise (Edward *et al.*, 2017), automatically placing online orders to refill the storage (Khan *et al.*, 2019), predict the quality of items in the storage (Rajeswari *et al.*, 2022), and reducing food waste (Srinivasan, 2022).

Meanwhile, these additional and smart functions are enabled by several up-to-date technologies and systems, comprising a sensing device, a controller module, and a transmission module. Common sensing devices that are commonly included in the system are a camera (Khan *et al.*, 2019), a weight sensor (Khan *et al.*, 2019), an infrared sensor (Khan *et al.*, 2019; Zhongmin & Yanan, 2018), an air quality sensor (Zhongmin & Yanan, 2018), a pressure sensor (Zhongmin & Yanan, 2018), a temperature sensor (Edward *et al.*, 2017; Zhongmin & Yanan, 2018), a humidity sensor (Zhongmin & Yanan, 2018), a photodiode goods sensor (Edward *et al.*, 2017), and a barcode scanner (Edward *et al.*, 2017). Common controllers that have been used are Raspberry Pi (Edward *et al.*, 2017; Khan *et al.*, 2019), STM32 microcontrollers (Zhongmin & Yanan, 2018), and PIC18F67J60 microcontrollers (Gürüler, 2015). Whereas, the common transmission device that have been used in the smart cold storage system are computers, mobilephone, wifi, internet, and cloud storage (Hachani *et al.*, 2016; Khan *et al.*, 2019).

Based on the description above regarding research in the area of smart cold storage or refrigerators, it appears that existing research has utilized technological developments for the three main components of smart cold storage or smart refrigerators, namely sensing, controller, and transmission modules. Various purposes for using smart cold storage or smart refrigerators have been explored, including smart replenishment of storage, but no one has yet elaborated on the potential of the smart system, apart from replenishment and for energy efficiency purposes.

2.3 Inventory Management and AI in the Retail Sector

Activities in retail that can also have an environmental impact are inventory management activities. The decision related to the quantity of orders affects the frequency of delivery of goods from suppliers to retailers, so this has consequences for the use of fuel to transport goods. In addition, the decision to reorder the point in cold storage also determines the use of energy in cold storage and ultimately affects the cost of energy per stored product.

Because the determination of inventory policy requires data on demand, some researchers also conduct research on demand forecasts, for example, Benhamida *et al.* (2021). The forecasting process can become complex when dealing with irregular demand patterns (Tian *et al.*, 2021), such as intermittent demand and with high irregularity (lumpy demand) or low irregularity (intermittent demand) (Sarlo *et al.*, 2023; Syntetos & Boylan, 2005). Forecasting errors can be the cause of inaccurate inventory decisions and can lead to increased inventory costs, including transportation costs (Gustriansyah *et al.*, 2022). Several studies have developed forecasting methods for special conditions, such as irregular demand (Sarlo *et al.*, 2023; Tian *et al.*, 2021). Data is a factor that greatly influences forecasting; therefore, data analytic techniques can also support the forecasting process for certain needs (Lalou *et al.*, 2020).

Apart from forecasting, inventory monitoring systems also play an important role in inventory management. Ahmad *et al.* (2023) developed an Economic Order Quantity (EOQ)-based model by learning the effects of damage to environmentally friendly items under conditions of inflation and credit financing to minimize total costs. Kuiti *et al.* (2019) stated that collaboration between producers and retailers and a centralized supply chain tend to produce better environmentally friendly initiatives. Inventory management also aims to avoid stockouts caused by errors in inventory management and is a major challenge in retail (Sikkandhar *et al.*, 2023). Efficient inventory management is a key issue for achieving customer satisfaction and reducing the risk of lost profits (Milella *et al.*, 2020). Currently, there are several alternatives for more effective inventory monitoring, especially involving the use of technology, such as radio frequency identification (RFID), the Internet of Things (IoT), and the use of other sensors to read inventory (Atkins *et al.*, 2021; Casamayor-Pujol *et al.*, 2020; Tao *et al.*, 2022). Customers who lose their intention to buy are one of the biggest losses in the retail sector; therefore, methods are needed to manage and control inventory with appropriate policies to improve retail performance. One of the problems that retailers often face is stockouts, but to overcome this problem, a situation of excess inventory can also occur, which has an impact on increasing costs (Obot *et al.*, 2019). Several studies utilize and modify the classic EOQ method to determine optimal ordering or replenishment policies (Briseño-Oliveros *et al.*, 2019; Obot *et al.*, 2019). Given the many uncertainties that exist in a real system, determining inventory policy can also be done using simulation techniques. Sridhar *et al.* (2021) carried out a simulation technique to minimize inventory levels while maintaining service levels. Witthayapraphakorn & Jaijit (2023) also employed the simulation method to ascertain the ideal re-order point for meeting service levels. Another determination of inventory policy is to consider the level of demand, which is a function of the inventory space allocated for products on the shelves by modeling uncertainty in the level of demand with the aim of maximizing profit expectations (Srivastava *et al.*, 2023).

The development of an inventory policy with uncertain demand was also carried out by Saffari (2022), involving a profit function consisting of sales revenue, storage costs, shortage costs, and ordering costs. Sutrisno *et al.* (2023) developed an inventory policy involving supplier selection techniques aimed at minimizing total operational expenses by considering discounts and other uncertainty parameters. Bassamboo *et al.* (2020) conducted research to overcome the problem of inspection and replenishment of unrecorded inventory (phantom inventory) due to other factors such as spoilage, damage, expired products, and theft. In addition to cost-related objective functions, sustainability factors can also be considered in determining inventory policies. Paul *et al*. (2022) saw an increase in green retail practices at this time; therefore, they conducted research to determine the optimal replenishment time and level of concern for the environment. Another study involving the sustainability dimension of inventory problems was conducted by Gioia *et al*. (2023) on retail inventory management with perishable products.

Due to the development of AI, enthusiasm for AI in the retail sector is quite high, but there is uncertainty regarding where the best areas are to apply AI in the retail value chain and regarding the rate of return on investment (Oosthuizen *et al*., 2021). Rekha & Vijaykumar (2019); Benhamida *et al*. (2021); and Wang *et al*. (2023) discussed the AI application for demand forecasting. In addition, Li *et al*. (2023) and Qaffas *et al*. (2023) conducted research related to the use of AI to classify inventory for certain purposes. Another research study was conducted in the area of inventory management, especially related to reducing errors in conventional inventory monitoring systems (Agarwal *et al*., 2020; Milella *et al*., 2020; Sikkandhar *et al*., 2023). Recent research conducted by Kaynov *et al*. (2024) discussed AI applications to manage distribution systems between warehouses and retail.

From the description above, many people have conducted research related to inventory management in the retail industry. However, no one has attempted to find a direct relationship between decisions taken in inventory management and energy efficiency in the retail industry. Moreover, AI has been applied to enhance the operation of the retail sector, including in the inventory management area. However, the potential of integrating AI with IoT, inventory management, cold storage operations, and energy efficiency in the retail industry has not been studied yet by previous researchers.

3. PROPOSED FRAMEWORK FOR DEVELOPING SUSTAINABLE RETAIL USING IOT AND AI FOR INVENTORY MANAGEMENT

The proposed framework developed an inventory management model and application designed to notify retail managers for the prompt replenishment of merchandise in cold storage to monitor inventory levels consistently. In the proposed method, a CNN model categorizes visual data to generate restock notifications. The energy costs associated with commodities in cold storage influence the classification of inventory replenishment. The proposed inventory management model consists of two phases: development and implementation. Figure 1 illustrates the development period. The development phase initiates with data collection, employing sensors and a microprocessor to document cold storage activity. Retail managers replenish stock concurrently with customer purchases, leading to a decrease and increase in inventory, respectively. The proposed framework retains the subsequent data: 1) opening and closing times of cold storage doors, 2) electrical energy consumption, 3) temperature within cold storage, 4) weight of products, and 5) images of products. The neural network is subsequently trained for image classification. Image categorization serves as a method for monitoring cold storage inventories. The Convolutional Neural Network (CNN) algorithm is employed for image classification. The CNN model will undergo training using images obtained during the data collection phase. The image dataset will be categorized into two classes: backfill and no backfill. The basis for dividing classification classes is explained in the next section.

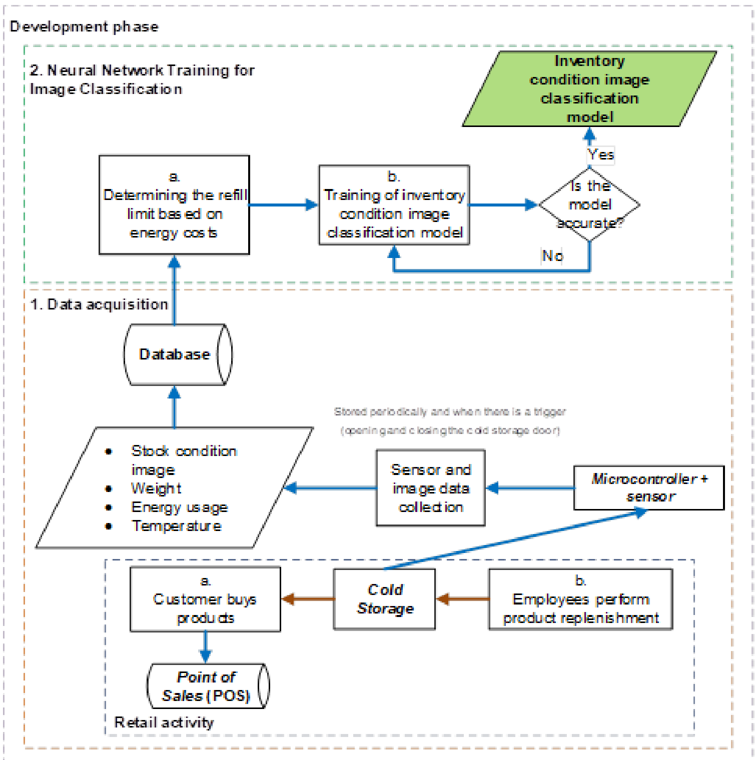


Figure 1 AI and IoT-based inventory management model and application development phase.

After the CNN model has been successfully trained, the next phase is the implementation phase, which is shown in Figure 2. The implementation phase only uses image input from the camera. Therefore, in this step, weight, energy, and temperature sensors are no longer used. The camera installed in the cold storage takes pictures of the inventory when there is a trigger from the sensor installed on the door to determine whether there is activity of closing the cold storage door. The inventory images are classified using the CNN model. When the classification results show that the inventory image requires replenishment, the application sends a notification automatically wirelessly or via the internet in a certain format to the decision maker.

Cold storage always maintains the temperature so that it is always at the expected temperature (set point). Figure 3 is an example of a cooling machine's work cycle to maintain temperature. Cold storage turns the cooling machine on and off periodically, causing the temperature to drop gradually. When there is an increase in temperature, the cooling engine will run for a longer duration so that the temperature can drop more quickly. It should be noted that each cold storage may have a different working system to maintain temperature. In the proposed model, the electrical power consumed by cold storage is assumed to be constant using the average power per unit time with energy costs (Blazek, 2011; Fett *et al.*, 2019), which can be calculated using Equation 1.

$$c_s = \left(\frac{W}{1000}\right) \times c_e \tag{1}$$

Every product stored in cold storage will bear energy costs. The amount of energy costs per unit time by each unit is influenced by the amount of product stored and can be determined using Equation 2.

$$c_u = \frac{c_s}{I} \tag{2}$$

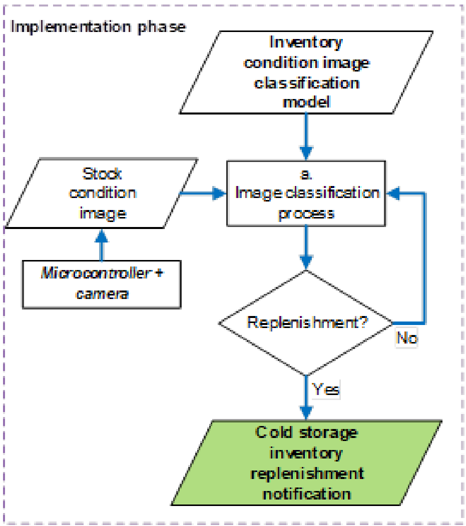


Figure 2 AI and IoT based inventory management model and application implementation phase.

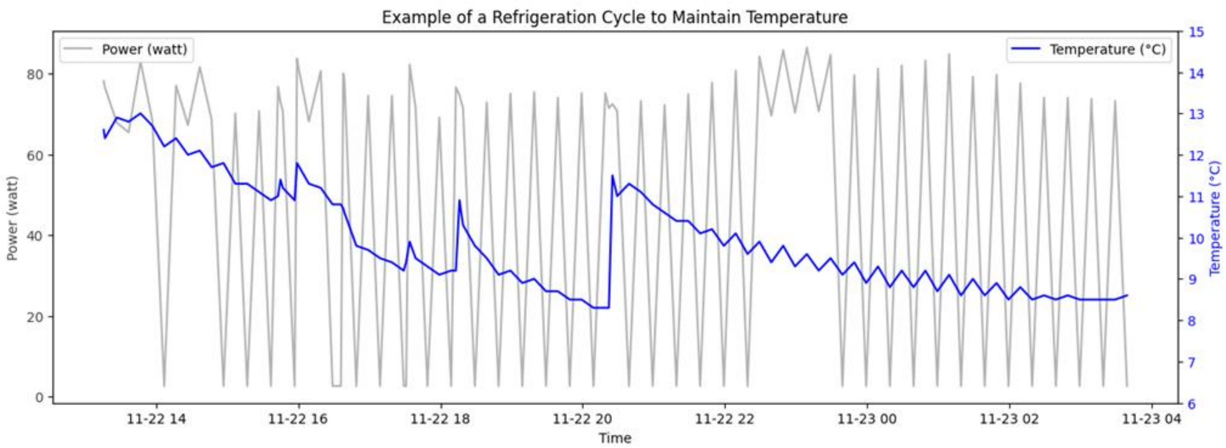


Figure 3 Example of refrigeration cycle to maintain temperature.

The energy costs per unit of time incurred by each unit are greater when the product stored is less, and vice versa. The change in energy costs per unit per unit time is depicted in Figure 4 and forms an exponentially decreasing curve (Stewart, 2012).

Based on Figure 4, the function of changing energy costs per unit per unit time can be written in Equation 3.

$$c_u(I) = a.e^{-bI} \tag{3}$$

Inventory replenishment limit is the number of products stored in cold storage that have a decline rate below a specified threshold. Therefore, the inventory replenishment limit can be determined by calculating the inventory level when the first derivative of the energy cost function per unit per unit time is at the threshold of the energy cost growth rate

(Equation 4). The graphical illustration of Equation 4 is also presented in Figure 4, where the first derivative of energy cost function value at certain point of inventory value, i.e. at I equal to R, is the gradient of the tangent line (M) at that point (Stewart, 2012).

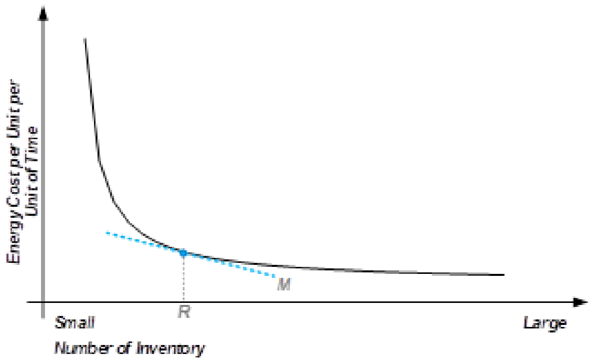


Figure 4 Change in energy cost per unit per unit of time against the amount of product stored.

$$\left.\frac{\partial c_u}{\partial I}\right|_{I=R} = M \tag{4}$$

Because the energy cost per unit time is a decreasing curve, M has a negative value. This is used as a basis for dividing classification classes in CNN model training.

4. CASE STUDY

A common problem facing the retail industry is that there are goods that need to be stored in cold storage, i.e. items being displayed inside the showcase. The operations of the showcase are related to the business process of customer purchase, which is reducing inventory, and inventory replenishment, which is increasing the inventory level. The replenishment process usually uses a decision model for inventory management and does not consider energy efficiency. Using AI and the idea of earlier smart cold storage, the framework suggested in Section 3 should help with making better decisions about when to restock, while also taking energy efficiency into account.

As a case study of the general problem mentioned above, we implement the proposed framework for a small retail store that is called Serviens Mart. This retail store uses a showcase used to store dairy products.

The case study is written according to a framework consisting of the development phase in Figure 1 and the implementation phase in Figure 2. At the end of the application development phase, a restock value will be determined. This restock value shows the minimum amount of milk in the refrigerator, which causes the energy costs per unit of product stored to be the smallest. At the end of the implementation phase, an actual stock value will be obtained. Furthermore, the application or software will send a notification to the store manager for replenishing goods in cold storage if this actual stock value is less than restock value. In other words, an automatic notification will appear when the number of items in the refrigerator reaches the restock value.

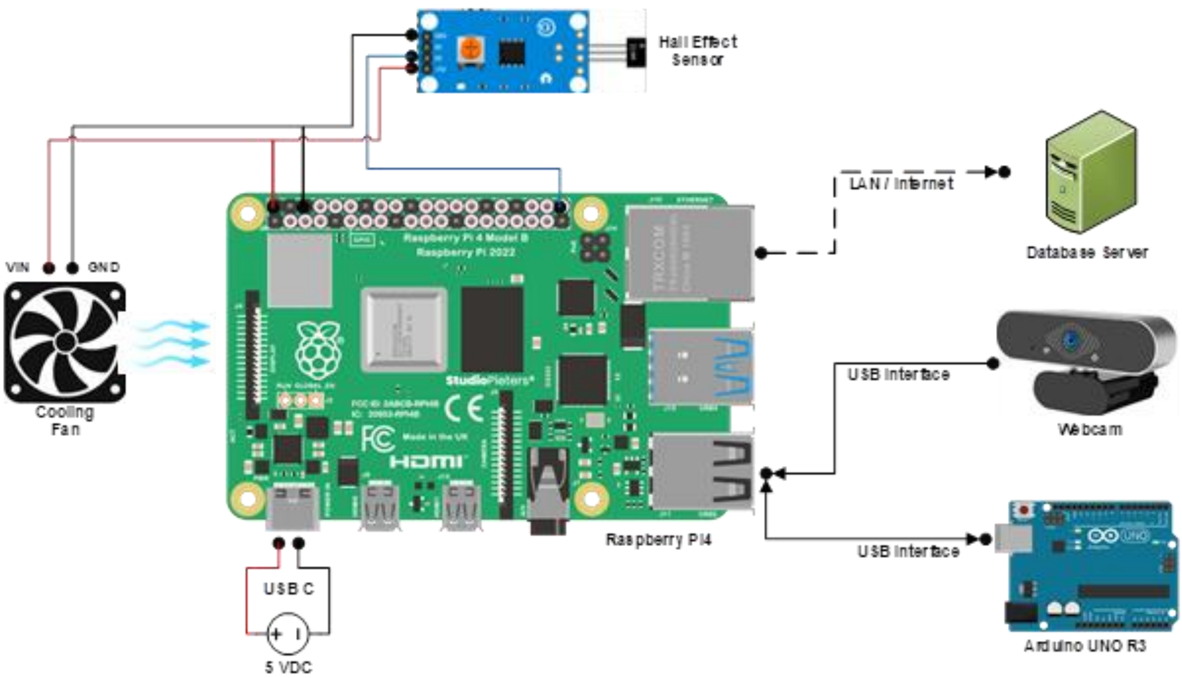


Figure 5 Raspberry pi 4 wiring diagram.

4.1 Sustainable Retail Related to Energy Issues

4.1.1 Hardware Assembly

Before entering the development phase in Figure 1 this phase begins with assembling the processing devices and sensors used to collect data and implementing AI and IoT-based inventory management models and applications. The processing devices used in this case study are the Raspberry Pi 4 Model B 8 Gb and the Arduino UNO R3 ATmega328P. Figure 5 and Figure 6 show wiring diagrams used in this case study. In its implementation, the processing device can be replaced with a different type by ensuring that the device can run the Python programming language, has GPIO pins for reading sensors, and can handle image classification models. The wiring diagram must also be adapted to the device used.

Raspberry Pi is planned as a device to send sensor data read by Arduino to a database server and to carry out image classification activities. Figure 6 shows the devices connected to the Raspberry Pi. There is a hall effect sensor, which is used to detect the condition of the cold storage door (open or closed), a camera to take pictures of inventory in the cold storage, as well as a connection to the network via ethernet or WiFi and Arduino via USB.

Arduino is planned as a device to read data from various sensors, which will later be sent to the Raspberry Pi. Figure 6 shows the devices connected to the Arduino. There are sensors to read inventory weight, a temperature sensor (DHT 22), and an AC electricity measurement sensor (PZEM-004T), as shown in Figure 7.

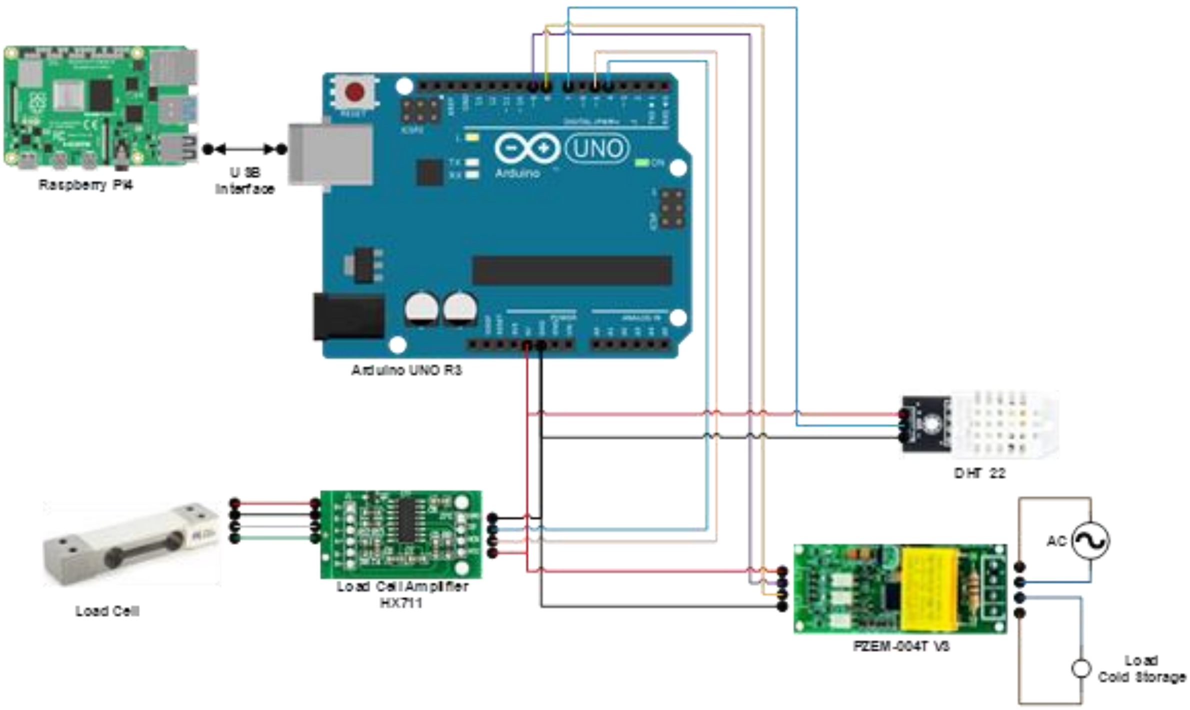


Figure 6 Arduino UNO wiring diagram.

(Camera)

(Load Cell)

(Hall Effect Sensor)

(Temperature Sensor)

(AC measurement sensor)

Figure 7 Sensor's placement.

4.1.2 Data Acquisition

The data acquisition stage is used to collect data from sensors that have been installed in cold storage. In this case study, the database used is MySQL. Other SQL-based databases can also be used. The data acquisition process is carried out every certain period and when there is a trigger from the opening and closing of the cold storage door. Table 1 shows examples of data that was successfully acquired. There are timestamp values, AC electrical sensor readings (voltage, current, power, energy, frequency, and pf), temperature, humidity, image storage address, and condition of the cold storage door.

Table 1 Example of data acquired from the sensor readings.

Id	Timestamp	Weight	Voltage	Current	Power	Energy	Frequency	Pf	Temperature	Humidity	Picture	Doorstate
2050	11/6/2023 9:14	4.15	216.6	0.03	2.6	117.711	50	0.41	9.4	34.7		
2051	11/6/2023 9:24	4.15	215.9	0.53	64.3	117.722	50	0.56	9.1	19.7		
2052	11/6/2023 9:34	4.16	216.4	0.56	73.9	117.727	50	0.61	9.4	30		
2053	11/6/2023 9:37	3.93	216.4	0.54	69.1	117.729	50	0.59	9.3	26		open
2054	11/6/2023 9:39	3.92	216.5	0.54	66.4	117.732	50	0.57	9.2	28.9	collected_picture/ 20231106-093909.jpg	close
2055	11/6/2023 9:44	3.92	217.7	0.03	2.6	117.735	49.9	0.4	8.9	23		
2056	11/6/2023 9:54	3.93	218	0.55	69.5	117.742	50	0.58	8.8	25.2		
2057	11/6/2023 10:04	3.92	217	0.03	2.6	117.747	50	0.4	8.7	30		
2058	11/6/2023 10:14	3.93	216.1	0.54	65.4	117.756	50	0.56	8.6	21.7		
2059	11/6/2023 10:24	3.92	215.1	0.03	2.6	117.759	50	0.42	8.8	34.3		

4.1.3 Training A CNN Model for Image Classification

Before training the CNN model, the first step is to prepare the image dataset by dividing it into two classes, namely requiring refilling and not requiring refilling. The recharging limit is determined based on Equation 4. It is known that cold storage requires an average electrical power of 39.87 watts. Therefore, if the cost of electricity per kilowatt-hour (kWh) is Rp 1444.7 (assuming it follows the B-2/TR class tariff by electricity provider company) (PLN, 2024) or approximately 10 cents USD, then the cost of electrical energy required by cold storage can be determined using Equation 1.

$$c_s = \left(\frac{39,87}{1000}\right) \times 1444,70$$

$$c_s = Rp\ 57,6\ /kWh$$

The cost of electrical energy needed for cold storage is Rp 57.6 per kWh. Cold storage electrical energy costs are then used to determine changes in energy costs borne per unit per hour using Equation 2. It is assumed that cold storage has a storage capacity of 15 units. Changes in energy costs per unit per hour are presented in Table 2 and depicted in the graph in Figure 8.

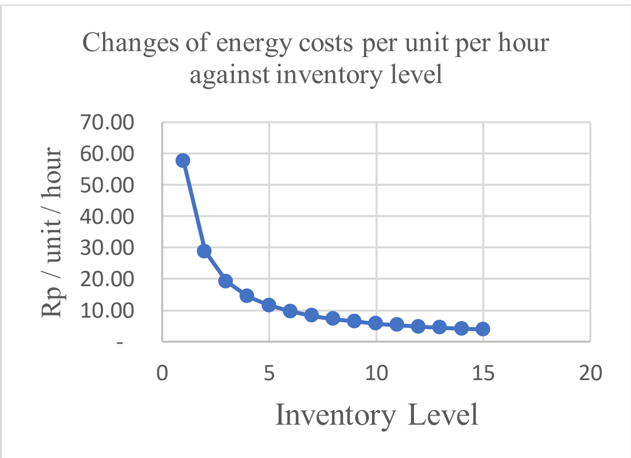


Figure 8 Graph of energy costs per unit per hour changes against inventory level.

Table 2 Changes of energy costs per unit per hour versus inventory level.

Inventory Level (unit)	Energy cost per unit per unit hour (Rp/unit/hour)
1	57.60
2	28.80
3	19.20
4	14.40
5	11.52
6	9.60
7	8.23
8	7.20
9	6.40
10	5.76
11	5.24
12	4.80
13	4.43
14	4.11
15	3.84

By using the SciPy library in Python, the exponential equation formed based on Figure 9 is presented in Equation 5.

$$c_u(I) = 76,302e^{-0,386I} \quad (5)$$

The replenishment limit is determined based on the inventory level which is at the decline rate threshold as in Equation 4. This stage determines the decline rate threshold of -1.$76,303.-0,386.e^{-0,386I}=-1$

$$I \approx 9\ unit$$

When the decline rate threshold is -1, then the replenishment limit occurs when the inventory reaches 9 units. An illustration of determining the recharge limit is shown in Figure 10. The reduction rate threshold used will be re-verified at the evaluation stage using simulation to produce an optimal objective function.

The backfill threshold is then used to divide the dataset into two classification classes. To make it easier to identify the number of products in an image, a weight variable can be used. This case study uses a single product weighing around 200 gr/unit. So the refill limit when converted into weight units is ≈ 1.8 kg. Figure 10a displays an example of an image classified as not requiring recharging and Figure 10b displays an example of an image classified as requiring recharging. The total images used as a training dataset were 918 images with 378 images classified as the class not requiring refilling and 540 images classified as the class requiring refilling. The image dataset is then subjected to initial processing including image sharpening, converting to black and white, border detection, and image cropping. The initial processing results are shown in Figure 11.

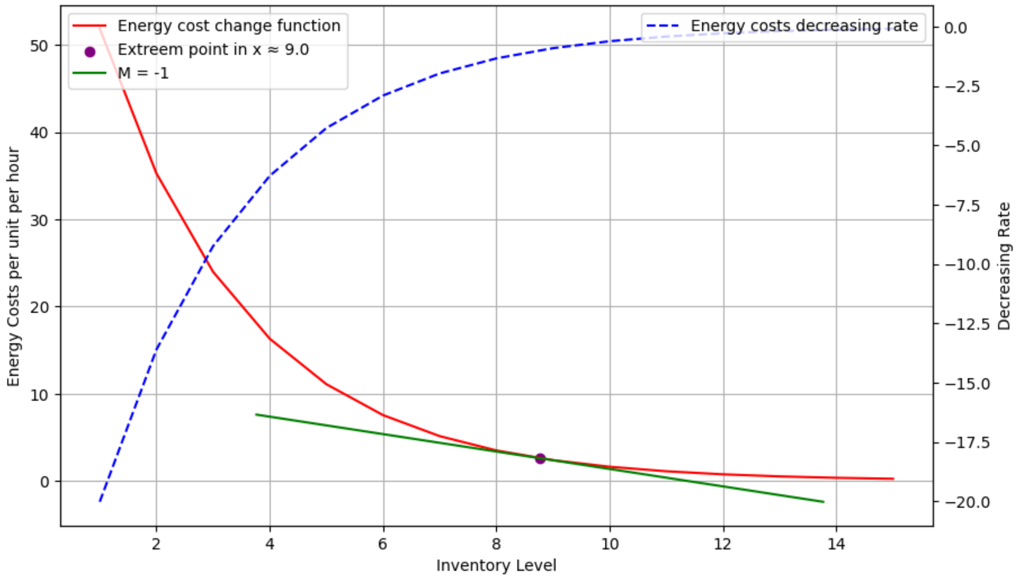


Figure 9 Replenishment points based on energy costs.

(a) **(b)**

Figure 10 Example of inventory images.

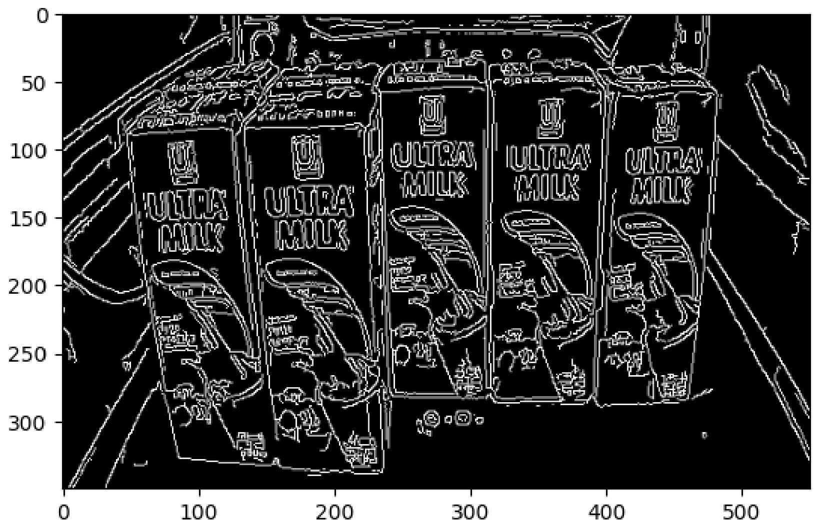


Figure 11 Result of image preprocessing.

To train the CNN model, the image dataset was loaded using the Keras library in Python into batch form and converted to a size of 360x360 pixels. There were 29 batches formed. The batch is divided into 70% for training, 20% for validation, and 10% for test. Next, the CNN model is trained using the prepared dataset.

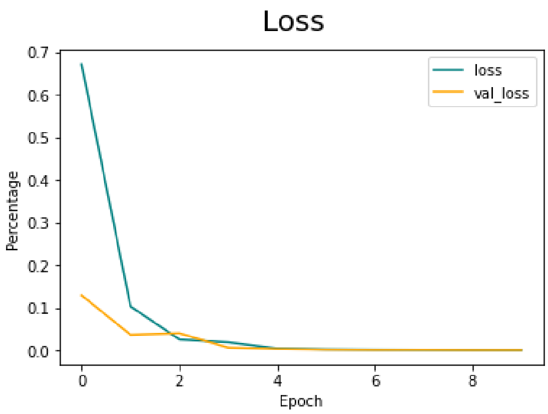
The development and optimization of the CNN model proceeds as follows. We selected Singh's (2019) CNN model as the basis model and parameter set. A process for tuning the model parameters was conducted to achieve accuracy and efficiency of the model. A combination of the following parameters was tested, in which two different values were selected for each parameter: (i) number of convolution layers (2 and 3), (ii) batch size (16 and 32), (iii) activation function (ReLU-sigmoid and ReLU-softmax), and (iv) number of epochs (10 and 20). It is also noted that the Adam optimizer is used in the model with its default learning rate, which is equal to 0.001.

A full factorial design was conducted to optimize the model parameters, in which the computational time, best accuracy, and number of epochs when the best accuracy is achieved are recorded. It is reported here that all the combinations can achieve the same value of best accuracy, which is equal to 1. It is noted that this accuracy can be achieved because this experiment uses factory-made products that have uniform shapes, dimensions, and appearance. Therefore, to select the best model parameters, an efficiency measure is introduced, which is a ratio of the sum number of epochs when the best accuracy is achieved with the total number of epochs, then multiplied by its computational time. Based on the minimum ratio, the following is the CNN model selected in this case study.

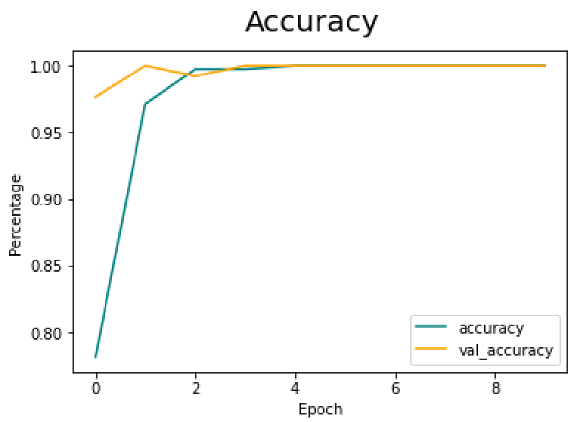
Table 3 Model CNN convolution layer.

Model CNN: Convolution Layer	
1	model.add(Conv2D(16, (3,3), 1, activation='relu', input_shape=(360,360,3)))
2	model.add(MaxPooling2D())
3	model.add(Conv2D(32, (3,3), 1, activation='relu'))
4	model.add(MaxPooling2D())
5	model.add(Conv2D(16, (3,3), 1, activation='relu'))
6	model.add(MaxPooling2D())
7	model.add(Flatten())
8	model.add(Dense(256, activation='relu'))
9	model.add(Dense(1, activation='sigmoid'))

The results of model training with the selected parameters are presented in Figure 12. The CNN model has a decrease in loss value (magnitude of prediction error) in the second iteration and tends to stabilize in subsequent iterations. The CNN model also produces accuracy values (how often the model produces correct predictions) which increases significantly until the second iteration and then tends to stabilize.



(a)



(b)

Figure 12 CNN model performance.

4.2 Implementation Phase

After the development phase is complete, in the implementation stage, the application for inventory management modeling is created according to the steps presented in Figure 2. In this stage, the inventory management models and applications that have been designed are then tested. The application will check the condition of the cold storage door. If the door opens then closes, the application will take a picture of the remaining inventory inside the cold storage. The images are then pre-processed and classified using the CNN model. If the inventory image is predicted to require replenishment, which is less than 9, the application will immediately send a replenishment notification to the retail operator. This notification is received by the retail operator, who is responsible for handling the replenishment of product inside the retail store. The notification urges the retail operator to fill it in until it is full. In this case study the notification is sent using Telegram application as an example of a medium for receiving notifications as seen in Figure 13.

It is undeniable that a product has a certain expiration date. Retailers can store product expiration dates on their point-of-sale (POS) system. This procedure ensures that the product remains safe for consumption prior to its placement in cold storage. When refilling products in cold storage, retailers generally follow a Standard Operating Procedure (SOP). Retail operators verify the expiration date of existing products before adding new ones to cold storage. Furthermore, the First in First Out (FIFO) concept guides the arrangement process. This arrangement enables the old product to be displayed in the front row, ensuring it will be taken first. Future research can be carried out by adding expiration date labels on product packaging before performing CNN technique. However, managing expired products using the previously mentioned manual procedures can still be done without an automatic system.

Figure 13 Example of replenishment notification.

5. RESULT AND DISCUSSION

The evaluation was carried out using an event-based simulation method to compare the proposed inventory management model and application with traditional inventory models using periodic reviews. The simulation was carried out based on sales activity data at the Serviens Mart retail. Sales activities at Serviens Mart are from 06.00 to 18.00. The simulation is carried out on one type of product with random demand levels. The assumption used is that out-of-stock events are not caused by ordering activities from retailers to distributors, but rather products that are not available in cold storage due to delays in the replenishment process. The flow of the simulation carried out can be seen in Figure 14.

There are differences in the inventory monitoring process between the periodic review model and the proposed inventory model. In the periodic review model (Figure 15a), inventory monitoring is carried out every certain time period. Meanwhile, in the proposed inventory model (Figure 15b), monitoring is carried out continuously by AI and IoT applications.

Table 3 shows the mathematical symbols used in the inventory simulation.

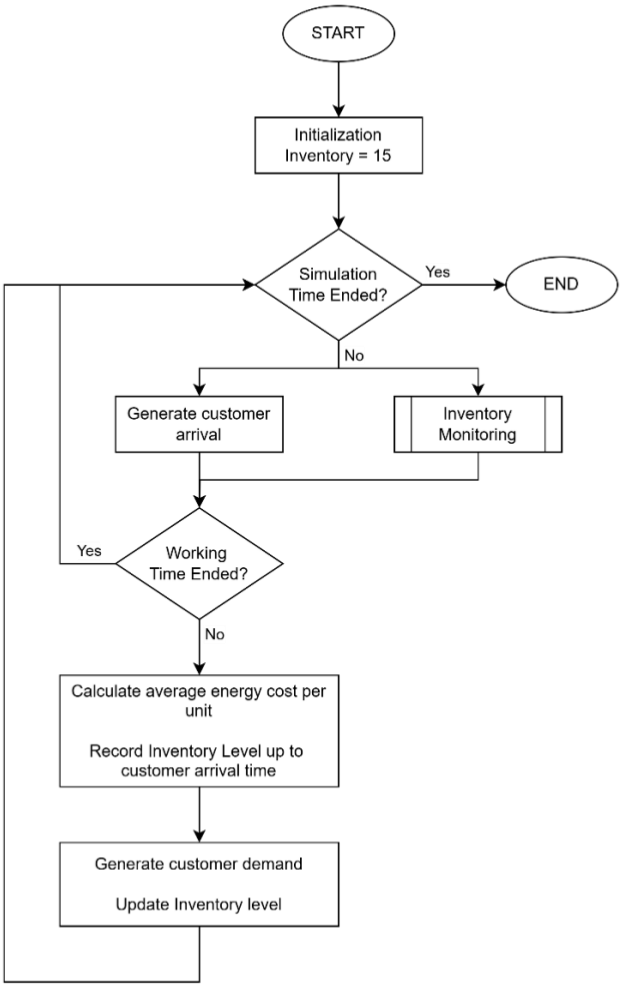
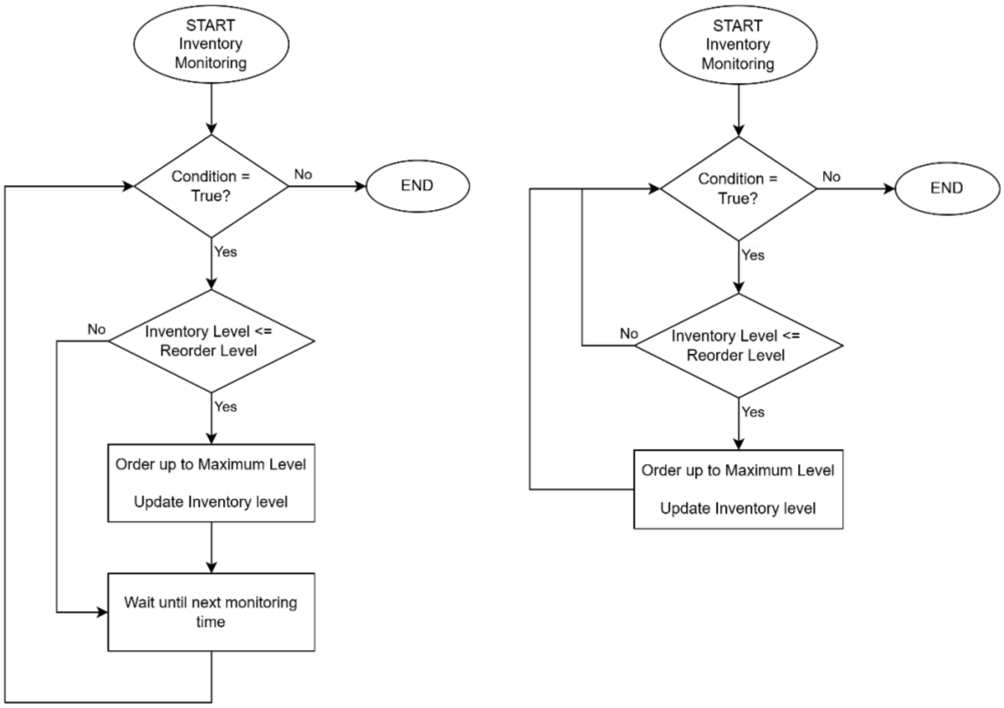


Figure 14 Inventory simulation flow.

In the inventory simulation, there is a parameter for the arrival rate between customers. The arrival rate between customers is known from data collected at the data acquisition stage. Data is filtered based on data that has the description "closed" in the "door state" column. The filtered data is then grouped by day and the number of closed-door events is calculated which describes the number of customers in one day. Next, the time between customer arrivals is obtained by dividing the total working hours per day by the number of customers in one day. Figure 16 shows a histogram of customer inter-arrival times.



(a) (b)

Figure 15 Inventory replenishment and review process.

Table 3 Mathematic symbols used in simulation.

Symbol		Description	Units
Parameter	r	Review period	(day)
	s	Replenishment point (periodic review)	(unit)
	S	Maximum inventory level	(unit)
	c_s	Cold storage energy costs per hour	(Rp/hour)
	c_e	Electricity costs per kWh	(Rp/kWh)
	c_u	Energy cost per unit per hour	(Rp/unit/hour)
	c_r	Replenishment and review cost	(Rp/review)
	C_h	Total holding cost	(Rp)
	C_i	Total penalty cost from cold storage energy wastage	(Rp)
	C_l	Total lost sales cost	(Rp)
	C_r	Total replenishment and review cost	(Rp)
	C_t	Total energy cost for replenishment	(Rp)
	I	Number pf products stored in *cold storage*	(unit)
	M	Threshold for the growth rate of energy costs per unit per hour	
	p_b	Purchase price per product	(Rp/unit)
	p_s	Selling price per product	(Rp/unit)
	P_0	Beginning inventory value	(Rp)
	P_p	Purchase value during simulation period	(Rp)
	P_T	Ending inventory value	(Rp)
	Q_d	Total demand	(unit)
	Q_s	Number of products sold	(unit)
	R	Replenishment point (proposed)	(unit)
	t_i	Total cold storage idle time	(jam)
	t_s	Average product storing time	(day/unit)
	t_t	Average time of cold storage reach set point temperature after replenishment	(hour)
	T	Number of simulation day	(day)
	W	Average cold storage power	(watt)
	μ	Average cold storage inventory level	(unit)
	λ	Customer interarrival rate	(arrival/second)
	Y	Total energy cost during storage per unit	(Rp/unit)
	Π	Total inventory cost	(Rp)

Next, the distribution was determined according to the time between customer arrivals using the Fitter library in Python and it was found that the time between customer arrivals followed an exponential distribution with an arrival rate of λ = 0.000095 customers per second (using units of seconds to simplify the simulation using the Simpy library in Python).

Each customer who comes can buy a different quantity. Determination of the number of purchases is carried out based on the probability of each possible number of requests shown in Table 4.

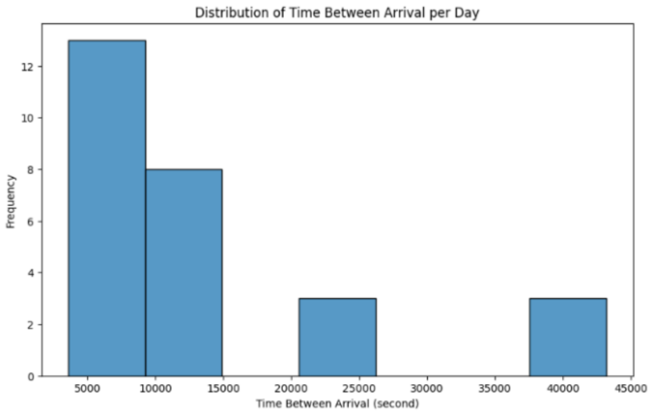


Figure 16 Histogram of time between arrival per day.

Table 4 Customer demand probability.

Demand (unit)	Probability (pdf)
0	0.171
1	0.690
2	0.101
3	0.039

The first objective function is the average total energy cost during storage per unit which is approximated by calculating the average energy cost per unit per hour multiplied by the average length of time the product is stored (Equation 6).

$$Y = c_u \times t_i \tag{6}$$

The average length of time a product is stored is determined by dividing the number of simulation days by the inventory turnover rate (ITO) (Equation 7 to Equation 9).

$$t_i = \frac{T_s}{ITO} \tag{7}$$

$$ITO = \frac{COGS}{\mu} \tag{8}$$

$$COGS = I_S + I_P - I_E \tag{9}$$

The second objective function is the total cost of inventory which consists of holding costs, lost sales costs, monitoring and replenishment costs, energy costs for replenishment, and energy waste penalty costs when the cold storage is empty. Storage costs are the energy costs to turn on cold storage during the simulation period (Equation 10).

$$C_h = c_s \times (T_i \times 24) \tag{10}$$

Lost sales costs are costs that arise when there is demand that cannot be fulfilled (Equation 11).

$$C_l = \left(Q_d - Q_s\right) \times P \tag{11}$$

Monitoring and refilling costs are costs that arise when there are monitoring or refilling activities in cold storage (Equation 12).

$$C_r = N_r \times c_r \tag{12}$$

Refilling energy costs are costs that arise due to cold storage working harder for a certain period to reduce the temperature after refilling activities (Equation 13).

$$C_t = N_r \times (c_s \times t_t) \tag{13}$$

The length of time for cold storage to reduce the temperature is obtained from sensor data. Refilling activity is shown by data that has an increase in the "weight" variable after the door opens and then closes. Figure 17 is an illustration of the calculation of time for cold storage to reach the set point temperature (7.6℃ with a tolerance of ±1℃) after refilling activities.

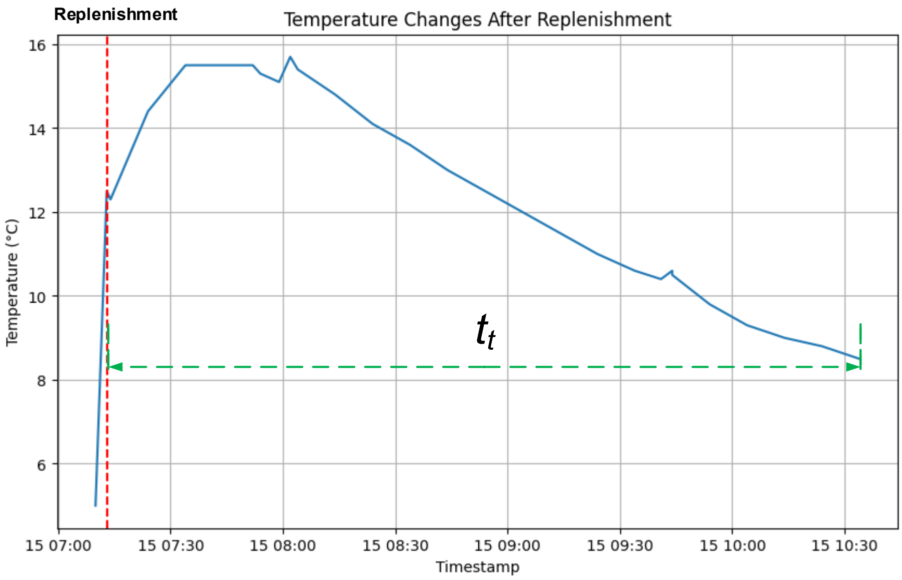


Figure 17 Temperature changes after replenishment.

Based on the data collected, the average time to reach the set point temperature is 4,695 hours. The final cost component is the penalty cost for wasting energy when the cold storage is empty or idle (Equation 14).

$$C_i = t_i \times c_s \tag{14}$$

Based on the cost components that have been explained, the total inventory cost can be determined using Equation 15.

$$\Pi = C_h + C_l + C_r + C_t + C_i \tag{15}$$

After compiling all the mathematical models used in inventory simulations, the next step is to run the simulation. In the periodic review model, simulations will be carried out on several combinations of parameters to determine optimal parameters that are appropriate to the case study and used as a comparison with the proposed inventory model. The list of parameters used in the periodic review model simulation is presented in Table 5.

Table 5 Parameter list for periodic review model.

Parameter	Value	Unit
r	1,2,3	day
s	1, 3, 5, 7, 9, 10, 12	unit
S	15	unit

Meanwhile, the simulation on the proposed inventory model was carried out by changing the threshold for the rate of reduction in energy costs from -0.5 to -4.5.

The simulation results of the periodic review model are presented in Table 6. The optimal periodic review model parameters are determined based on the parameters that have the lowest total inventory value. Therefore, the optimal parameters are (2,12,15) with a total cost of Rp 647,687.06,- (halfwidth: 1847.2). The periodic monitoring inventory model with these parameters produces a total energy cost per unit of Rp 437.27 (halfwidth: 1.62).

Meanwhile, the simulation results of the proposed inventory model are presented in Table 7. There are two objective functions considered, namely total energy costs per unit and total inventory costs. The simulation results are then depicted in the Pareto Front graph in Figure 18.

Table 6 Periodic review model simulation results.

Parameter	Total Inventory Cost (Π)	
	Average	Halfwidth
(1,1,15)	1,359,297.46	4,719.71
(1,3,15)	1,107,572.03	3,568.36
(1,5,15)	976,507.72	2,222.87
(1,7,15)	926,376.84	1,325.45
(1,9,15)	911,751.00	711.75
(1,10,15)	911,678.88	541.49
(1,12,15)	919,023.51	313.31
(2,1,15)	1,495,777.83	7,142.60
(2,3,15)	1,210,872.43	6,459.45
(2,5,15)	981,347.47	5,655.52
(2,7,15)	795,565.49	4,018.78
(2,9,15)	692,119.90	2,833.93
(2,10,15)	665,155.53	2,139.18
(2,12,15)	647,678.06	1,847.20
(3,1,15)	1,744,778.78	8,666.77
(3,3,15)	1,416,054.86	8,337.29
(3,5,15)	1,107,407.82	7,200.05
(3,7,15)	907,127.49	6,173.30
(3,9,15)	806,612.53	5,291.59
(3,10,15)	797,264.44	5,324.26
(3,12,15)	785,259.56	5,238.09

Table 7 Proposed model simulation results

Parameter Code	M	Total Energy Cost per Unit (Y)		Total Inventory Cost (Π)	
		Average	Halfwidth	Average	Halfwidth
U1	-0.50	343.39	0.90	914,122.67	1,656.29
U2	-0.75	358.58	0.91	791,190.40	1,310.78
U3	-1.00	349.07	0.91	708,160.67	1,116.45
U4	-1.50	366.72	0.97	648,226.73	957.93
U5	-2.00	358.12	0.94	602,901.82	860.40
U6	-3.00	379.93	1.06	567,038.26	746.25
U7	-4.50	374.96	0.96	538,588.77	667.53

Based on the Pareto Front graph, there are four parameters included in Pareto optimal. These four parameters are optimal parameters based on trade-offs between the two objective functions considered. Optimal parameters based on the Pareto Front mean parameters that cannot improve one objective function without sacrificing other objective functions.

The analysis continues with the weighting method to determine the parameters used as a comparison with the periodic review model. Table 8 shows the results of the weighting calculations for each parameter. The calculation assumes that both objective functions have the same weight. To avoid the dominance of objective functions that have large values, normalization is carried out on each objective function.

Based on the weighting method, the optimal energy cost reduction rate threshold is -2 (replenishment point: 7 units). These parameters produce total energy costs per unit of Rp 358.12 (half-width: 0.94) and total inventory costs of Rp 602,901.82 (half-width: 860.4).

The artificial intelligence and IoT-based inventory management model and application that was designed was successful in providing replenishment notifications when inventory levels were at the replenishment limit determined based on energy costs and was better than the periodic review model based on simulation results. Table 9 is a recapitulation of the optimal simulation results for the two models.

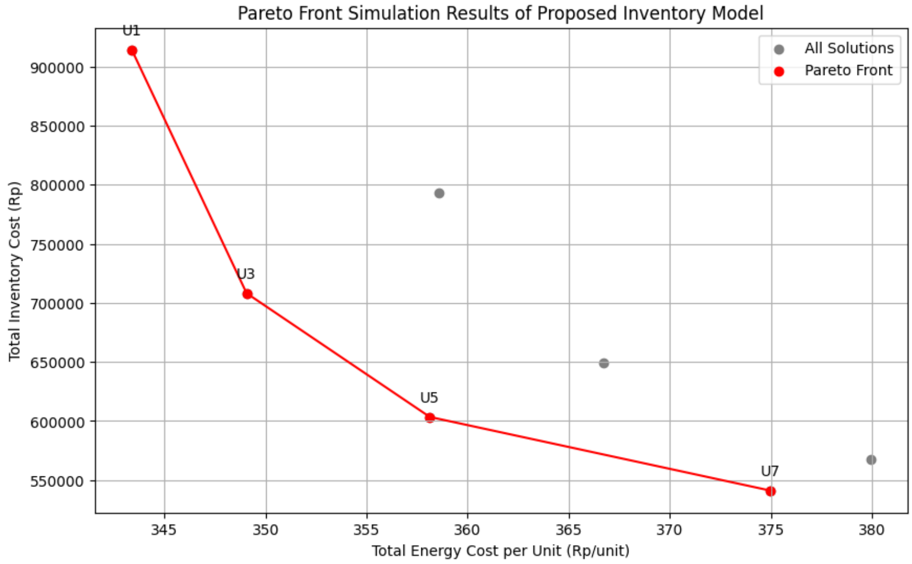


Figure 18 Pareto front simulation results of proposed inventory model.

Table 8 Score for each parameter based on weighted method.

Parameter Code	Normalized Total Energy Cost per Unit	Normalized Total Inventory Cost	Score
U1	1.00	0.00	0.50
U2	0.58	0.33	0.46
U3	0.84	0.55	0.70
U4	0.36	0.71	0.53
U5	0.60	0.83	0.71
U6	0.00	0.92	0.46
U7	0.14	1.00	0.57

The simulation results show a reduction of 18.1% in total energy costs per unit and 6.9% in total inventory costs. The reduction in total energy costs per unit occurs because the proposed inventory management model prevents cold storage emptiness by providing replenishment notifications; therefore, retail managers immediately replenish inventory. In addition, this model also takes into account replenishment limits based on the energy costs charged to products in cold storage, which are higher as the product quantity decreases. This limit is determined by taking into account the rate of decrease in energy costs per unit per hour. The graph in Figure 19 shows the trade-offs between total inventory costs and total energy costs per unit for each decline rate.

Table 9 Simulation results recapitulation.

Model	Total Energy Cost per Unit (Υ)		Total Inventory Cost (Π)	
	Average	Halfwidth	Average	Halfwidth
Periodic	437.27	1.62	647,678.06	1,847.20
Proposed	358.12	0.94	602,901.82	860.40

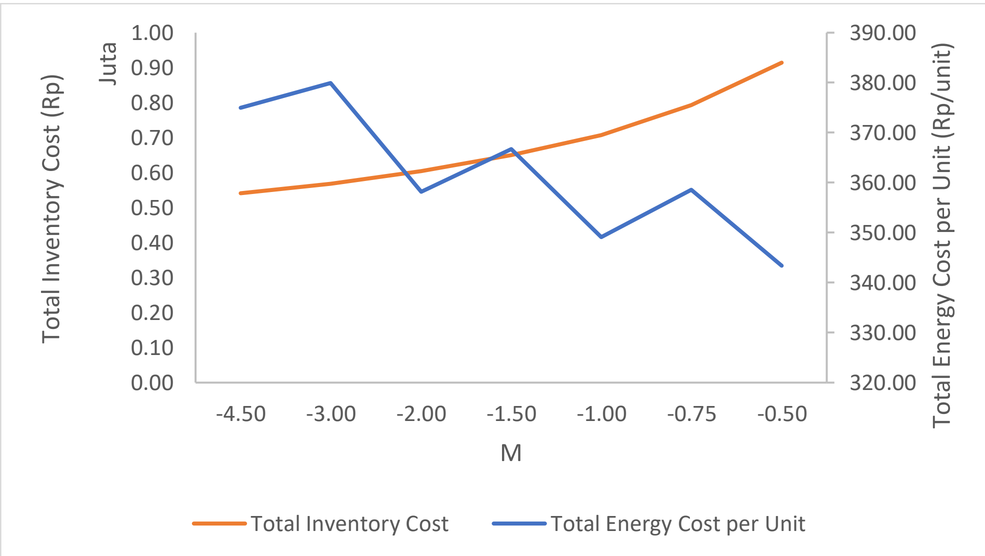


Figure 19 Trade-offs total inventory cost and total energy cost per unit.

Figure 19 shows that when the rate of decline in energy costs is sharp (the value of M is smaller), the replenishment limit in units is also lower, which causes the total cost of inventory to be lower but the energy costs per unit to increase. Conversely, if the rate of decline in energy costs is slower (the value of M is larger), the replenishment limit in units increases, so that energy costs per unit decrease, but total inventory costs increase. In addition, it was found that changes in energy costs per unit were not linear with changes in the value of M. There were several points, such as at -3, -1.5, and -0.75, where there was a significant increase followed by a decrease. This is caused by a slowdown in inventory turnover rates at these points, which causes energy costs per unit to increase during storage. This trade-offs graph helps establish the optimal threshold for the decline rate, that is, the point that strikes a balance between per-unit energy costs and total inventory costs.

In addition to reducing energy costs per unit, the proposed model also reduces total inventory costs. The proposed framework provides immediate notification when cold storage needs to be refilled, eliminating the need for periodic manual monitoring, which reduces the associated costs. The decrease in total costs also occurred due to reduced lost sales costs. In contrast to traditional models that rely on periodic replenishment, this model always maintains inventory with immediate notification, preventing cold storage emptiness and ensuring energy efficiency, so that energy consumption is reduced and costs per product are reduced.

6. RESULT AND DISCUSSION

This research succeeded in developing an inventory management model and application based on AI and IoT to support sustainable retail practices. This application provides notifications to retail managers to refill inventory in cold storage. These notifications are generated from inventory images that are processed using a pre-trained CNN model. Replenishment decisions are based on an optimized per-unit energy cost reduction rate threshold to reduce total energy costs and inventory costs. This model helps maintain inventory levels in cold storage so that it operates efficiently, reduces energy consumption, and avoids lost sales and energy waste.

The developed models and applications are also evaluated through event-based simulations to compare with traditional inventory management models based on periodic monitoring. The evaluation results show that this artificial intelligence and IoT-based model is more effective in reducing total energy costs per unit as well as overall inventory costs.

For further research, it is recommended to develop an artificial intelligence model using the object detection method to be able to calculate product quantities more accurately and handle dynamic refill limits. Apart from that, it is necessary to consider the tolerance of refilling time so that large cold storage management can be carried out more optimally.

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