Predictive Analytics for Cold Chain Break Detection

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Method Article

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Abstract

Perishable food deteriorates at any step in the cold chain due to various internal and external factors. The leading cause of deterioration is fluctuating ambient temperatures. An intelligent cold chain management system comprises proper observation and control of perishable food parameters from food safety. The current work develops a predictive model that considers critical factors like vehicle characteristics, initial and environmental temperature, method of loading and unloading the food in-vehicle, and measurement of Mean Kinetic Temperature (MKT). Predictive data analytics is carried out using machine learning algorithms for real-time forecasting of food quality at each stage of the cold chain. Machine learning models are a step forward in cold chain management that is more accurate and requires less computing time than traditional techniques such as CFD (Computational Fluid Dynamics) method, Kriging method, and capacitive heat transfer method. Thus, the developed system will avoid cold chain breakage caused by temperature abuse during transit. Experimentation with various perishable foods is being considered. The results are experimentally validated in real-time applications.

Highlights

The manuscript emphasized the significance of predictive analytics for cold chain break detection. Statistical analysis of food quality prediction is developed in cold chain considering various critical parameters such as initial temperature of food, measurement of Mean Kinetic Temperature (MKT), method of loading food in vehicle, environmental temperature, total travelling time, duration and frequency of unloading the food, and Vehicle size. The use of machine learning algorithms is a step forward for predicting food quality at each stage of cold chain and hence cold chain break detection.

Introduction

According to the NABARD (National Bank for Agriculture and Rural Development) report, India is a significant producer of a wide range of perishable foods. So it is essential to maintain the food quality and shelf-life during the transport stage of a cold chain. Cold chain management (CCM) involves packaging, storing, and distributing perishable food products from production to consumption. Temperature fluctuations during the cold chain significantly impact the food shelf life. Therefore proper refrigeration is required to extend the shelf life of perishable foods and ensure that consumers are received safe, high-quality food. Refrigeration use has increased in most developed and developing countries over the last few decades, and the perishable food product supply system is developing to maintain abreast (Nabard Report 2017). Food quality is based on the initial quality of the original food, various processes, and temperature fluctuations during the cold chain, and the packaging of food (Nodali Ndrahaa et al. 2018). Therefore, the quality characteristics of food, such as taste, color, flavor, and vitamin C level that deteriorates most rapidly in time, are considered for shelf-life testing of food. As a result, a sophisticated cold chain management system is being developed, including proper monitoring and control of perishable food parameters such as humidity, temperature, vibrations, and light throughout the cold chain (Hongmin Sun et al. 2016). An intelligent cold chain system refers to an information system that analyses environmental data and alerts producers and consumers to abnormalities (Mercier Samuel et al., 2017). Predictive analytics in a cold chain can be used to avoid wasting perishable items. It is one of the most effective techniques for assessing and mitigating cold chain risks (Abel et al., 2014, Khanuja et al., 2018).

The significance of food safety and quality in the cold chain with various solutions has been studied and analyzed. Unskilled operators, poorly designed refrigeration equipment, and improper placement of food packages in storage containers are responsible for temperature abuse in the cold food chain (Ndrahaa et al., 2018). Recent temperature monitoring and control technology have significantly contributed to the cold food chain, but no adequate data for predictive analytics is generated. Modern food preservation technologies for producing safe, high-quality frozen food have been proposed (Judith et al. 2008). (Nodali Ndraha et al., 2018) used data loggers to evaluate the temperature management system during transportation. A kinetic model has been developed to assess quality changes and estimate shelf life for various seafood without considering season variability and door opening frequency of cold trucks. Perishable food safety is highly dependent on freshness and can have severe consequences for human health. As a result, cold chain monitoring and control are required for trustworthy quality management and perishable food optimization at each step of the cold chain.

The main objective of the present work is to propose a predictive model for predicting the quality of perishable food by considering the parameters responsible for food quality degradation during the transportation stage of the cold chain. Furthermore, since the cold chain generates a large amount of experimental and numerical data, another objective is to use machine learning models to predict food quality and cold chain break alerts by anticipating time-temperature relationships during transportation.

Materials And Methods

Quality is a multifaceted aspect of food that significantly impacts consumer acceptance (Miriam et al., 2014). Numerous physiological phenomena and biological reaction kinetics play a significant role in food shelf-life in the case of perishable food (Subburaja et al., 2015). Furthermore, the cold chain contains food distribution from the cold storage to the consumer freezer. Therefore, evaluating perishable food quality is essential for the cold chain management.

Figure 1 depicts a cold chain management system built on an IoT platform. The temperature and humidity sensors installed inside the reefer continuously monitor the temperature and relative humidity. This real-time data is then extracted with the assistance of a data logger. At this stage, an attempt is made to calculate the Mean Kinetic Temperature (MKT), which will provide a precise measurement of the food's quality index. The data is then sent to the controller, which analyzed using machine learning algorithms. The system also provides the live location of cold reefers, and the analytics and corresponding statistics are sent to the appropriate person via a mobile app. With the assistance of this analysis, the concerned individual will take corrective action in the form of:

- Re-shipping before a damaged product arrives with the help of this analytic.

- Dispatching emergency crews to repair a cold chain breakdown at a warehouse or in logistics.
- Adjusting the thermostat to account for deviations that occurred on one leg of the journey.
- Rerouting the shipment if necessary.

The quality of perishable food is assessed in this work by incorporating a mathematical model of the perishable food quality index into machine learning algorithms.

Calculation of Quality Index

The rate of quality loss becomes temperature-sensitive at each stage (Kitinoja 2013). The deterioration rate constant (k) of food can be given by the Arrhenius equation that constitutes the universal gas constant (R), an absolute temperature (T), activation energy (E), and pre-exponential factor (A) (Mercier Samuel et al. 2017).

$$\mathrm{lnk} = \mathrm{lnA} - \frac{\mathrm{E_a}}{\mathrm{RT}}$$

1

The relationship between perishable food's shelf life (θ) and the constant deterioration rate is inverse. Eq. (2) shows that the shelf-life data is helpful for the approximation of activation energy values (Kale Ajay 2014).

$$\ln\left(\frac{\mathrm{k}}{\mathrm{k_1}}\right) = -\frac{\mathrm{E_a}}{\mathrm{R}}\left(\frac{1}{\mathrm{T}} - \frac{1}{\mathrm{T_1}}\right) = \ln\left(\frac{\theta_1}{\theta}\right)$$

2

The Q10 method is frequently used to calculate the temperature acceleration of shelf life. For example, when the temperature of food products is changed by 10°C, Q10 reflects the rise in the rate of deterioration (k). The following expression connects Q10 to the Arrhenius equation and the shelf-life model:

$$\mathrm{Q_{10}} = \mathrm{Exp}\left(\frac{10\mathrm{Ea}}{\mathrm{RT}(\mathrm{T}+10)}\right) = \frac{\theta \mathrm{T}}{\theta \mathrm{T}+10}$$

3

As a result, the value of Q10 is used to calculate Accelerated Aging Rate (A), which is required for calculating Accelerated Aging Time Duration (AATD) of perishable food as:

$$\mathrm{AATD} = \mathrm{DesiredRealTime}/\mathrm{A}$$

4

Where A = Accelerated Aging Rate given by

$$A = Q_{10}\left(\frac{Te - Ta}{10}\right)$$

5

Where Te is elevated Temperature and Ta is ambient temperature.

The final quality retained by frozen food after each visit is calculated as follows:

$$\%\text{Qualityretained} = \left(1 - \sum_{1}^{m} \frac{t_{T_i}}{\theta_{T_i}}\right)100 = 1 - \frac{t_{tot}}{\theta_{Teff}}$$

6

The overall effect of temperature changes on perishable food during transportation is stated in Mean Kinetic Temperature, one of the essential components of the proposed model (MKT). The MKT is the total effect of temperature differences, taking into account food biochemical changes (Emenike et al. 2016). The MKT temperature is the ideal temperature to sustain during various cold chain procedures.

$$T_k = \frac{{}^{-E_a}/_{R}}{\ln\left(\frac{e^{{}^{-E_a}/_{RT1}} + e^{{}^{-E_a}/_{RT2}} + \cdots + e^{{}^{-E_a}/_{RTn}}}{n}\right)} \qquad (7)$$

Thus, the MKT calculation is used by the Food and Drug Administration (FDA) to determine whether the temperature limit of perishable food was exceeded during transportation. However, maintaining the proper storage temperature during transit is extremely difficult due to variable vehicle features (Indumathi et al., 2018, Zakeri et al., 2018). As a result, the calculation of heat transfer coefficient (h) in terms of thermal capacity (W) and mean surface area (S) of an insulated vehicle taking into account both inside and outside temperature (T) (Novaes et al. 2015) is defined as:

$h = WS^{-1}\Delta T^{-1}$ (8)

The value of h should be h < 0.4W/m2K or -272.75W/m2°C according to the ATP agreement.

As a result, the cooling capacity W is computed as follows:

$$W = h.\,S.\,\Delta T.1.75$$

9

1.75 is the minimum safety factor according to ATP agreements.

Predictive Data Analytics

The statistical model is used for predictive data analytics in terms of food quality. Machine learning algorithms are used to predict food quality and cold chain break detection. For the analysis data, possible formalizations are presented below:

$\mathrm{f(Tp(t))} = \int_{\mathrm{t1}}^{\mathrm{t2}} \mathrm{f(Tp(t))dt}$ Product temperature is calculated in the specific time intervals

$\mathrm{Tp(t)} > Tc$ How many times does the product's temperature rise above the crucial level?

$\mathrm{MKT} > MKTc$ Micro-biological growth and vitamin 'C' loss simulation.

$\mathrm{Rh\%} > \mathrm{Rhc\%}$ No. of times, the relative humidity in the container exceeds the critical humidity.

Thus, machine learning methods are employed to detect temperature changes in transit and cold chain breaks. In addition, predictive data analytics is used to ensure food quality throughout the cold chain.

For obtaining essential information from the cold chain, the following machine learning methods are utilized as a data mining tool.

Decision Tree Regressor:

A decision tree is a supervised learning algorithm. It applies to categorical as well as continuous input and output variables. We used the Decision Tree Regressor for prediction because our response variable is continuous.

Random Forest regressor:

As a fundamental learning model, Random Forest uses several decision trees. Instead of depending on individual decision trees, the main idea is to aggregate numerous decision trees to determine the outcome. A Random Forest is an ensemble technique that uses several decision trees to solve regression and classification tasks.

KNN regressor:

The KNN algorithm is a supervised machine learning method that may be used to solve classification and regression predicting problems. It predicts the values of new data points based on 'feature similarity.'

For better accuracy ensemble technique is used for the above machine learning algorithms. Ensemble Learning is a strategy for making better decisions utilizing many machine learning models. For each method, two strategies are employed, and the final prediction is made using the "VOTING" ensemble technique. The first step is to use the bagging technique, which involves aggregating the findings of various models and making a final prediction. Second, to improve accuracy, boosting is performed sequentially. Finally, the average of all models is calculated using the voting process.

Results And Discussion

Initially, the milk cold chain database was updated to meet the standards. When local travel begins from the depot, perishable food is deemed milk with an initial temperature of 4°C.With the real-time study, the total travel time is assumed to be 24 hours (1440 minutes) with a door open frequency of 10 times and 10 minutes. A slight temperature excursion is assumed after each 10 min, and then the temperature difference is calculated (Donald E. et al., 2015). Next, Q10 values are calculated according to the Arrhenius equation. Finally, the accelerated Aging Time Duration (AATD) of perishable food is calculated using Q10 values. Three different cases are considered while loading the cargo. Three different vehicles of different surface areas are considered with a constant 'h' value. Mean Kinetic Temperature (MKT) and milk quality retention are calculated using machine learning algorithms after each visit.

When perishable food is placed into a cold vehicle, the following cases are considered.

Case 1

The food is loaded directly into the vehicle with no or very little temperature change.

Case 2

The food is loaded in a room at 10° C temperature.

Case 3

The food is loaded at an ambient temperature of 25°C.

The proposed mathematical model is implemented in machine learning algorithms.

Case 1

Figure 2 shows variation in temperature concerning time. As cargo is brought directly from the cargo, temperature variation is slight.

Figure 3 shows that the Accelerated Aging Time Duration (AATD) of perishable food decreases as the temperature increases. Because AATD aims to store food in a controlled environment to avoid deterioration; hence if that controlled temperature changes, AATD starts to decrease.

Figure 4 shows the relation between temperature and cooling capacity for vehicles of a mean surface area of 26.9 m^2, 28.3 m^2, and 34.6 m^2, respectively. More cooling is required as the surface area of the vehicle is increased.

Case 2

Figures 5 and 6 show variations in temperature concerning time and temperature versus Accelerated Aging Time Duration (AATD). As cargo is brought via a room (at 10°C temperature), the temperature variation is higher than in case 1.

Also, the cooling capacity required is more for different vehicles than case 1, as shown in Fig. 7.

Case 3

As the product is transported through a 25°C ambient temperature, the temperature variation is the highest, shown in Fig. 8. Also, the Accelerated Aging Time Duration decreases as the temperature increases, as shown in Fig. 9.

The cooling capacity required is the highest for different vehicles, as shown in Fig. 10.

Table 1 shows the MKT measured and quality retained after each client visit.

Table – 1 Mean Kinetic Temperature and Quality retained in %

Client Visits	MKT after each visit(°C)	Time (hours)	Quality retained (%)
1	5.13	2	99.52%
2	6.75	3.3	98.95%
3	7.95	4.8	98.33%
4	8.15	8.6	97.73%
5	8.17	10	97.75%
6	7.75	13.3	96.24%
7	7.72	16.6	96.18%
8	7.43	20	93.70%
9	7.64	21.6	93.18%
10	7.76	24	93.7%

Since the cold chain generates a large amount of data, machine learning appears useful for analytics. For example, the developed model can now predict the time-temperature relationships at each cold chain point. Other perishable foods, such as meat, cheese, grapes, and beans, are also included in the model. Real-time field visits to cold storage and logistics empirically validate the proposed work's results. In addition, it has been discovered that machine learning techniques are more accurate and take less time to compute than traditional CFD and capacitive heat transfer methods.

Table 2 depicts a comparison of the implemented algorithm.

Table – 2 Comparative analysis of implemented algorithm

Parameters	Decision Tree Regressor with boosting	Random Forest Regressor with boosting	KNN regressor with boosting
Accuracy percentage)	99.93%	99.98%	72.10%
Training time in seconds	0.0060 sec	0.24 sec	0.0055 sec
Predicted time in seconds	0.0059 sec	0.17 sec	0.0096 sec
Mean Square Error	0.003055	0.0006175	1.2177

Conclusions

The present study proposed a mathematical model to determine the quality index of perishable food during transportation. It is observed that various parameters like the method of loading, duration, frequency of unloading, vehicle characteristics, and duration of traveling are responsible for temperature abuse during transportation. The proposed model predicts the quality retained at each step by adopting the measurement of Mean Kinetic Temperature. Machine learning algorithms are used as a data mining tool to predict quality. The random forest regressor with boosting ensemble technique gives the highest accuracy of 99.98% compared with the Decision tree regressor and KNN regressor with ensembling. On the other hand, the KNN regressor gives the lowest accuracy of 72.10%.

Declarations

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Conflicts of Interest

No conflict of interest.

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Figures

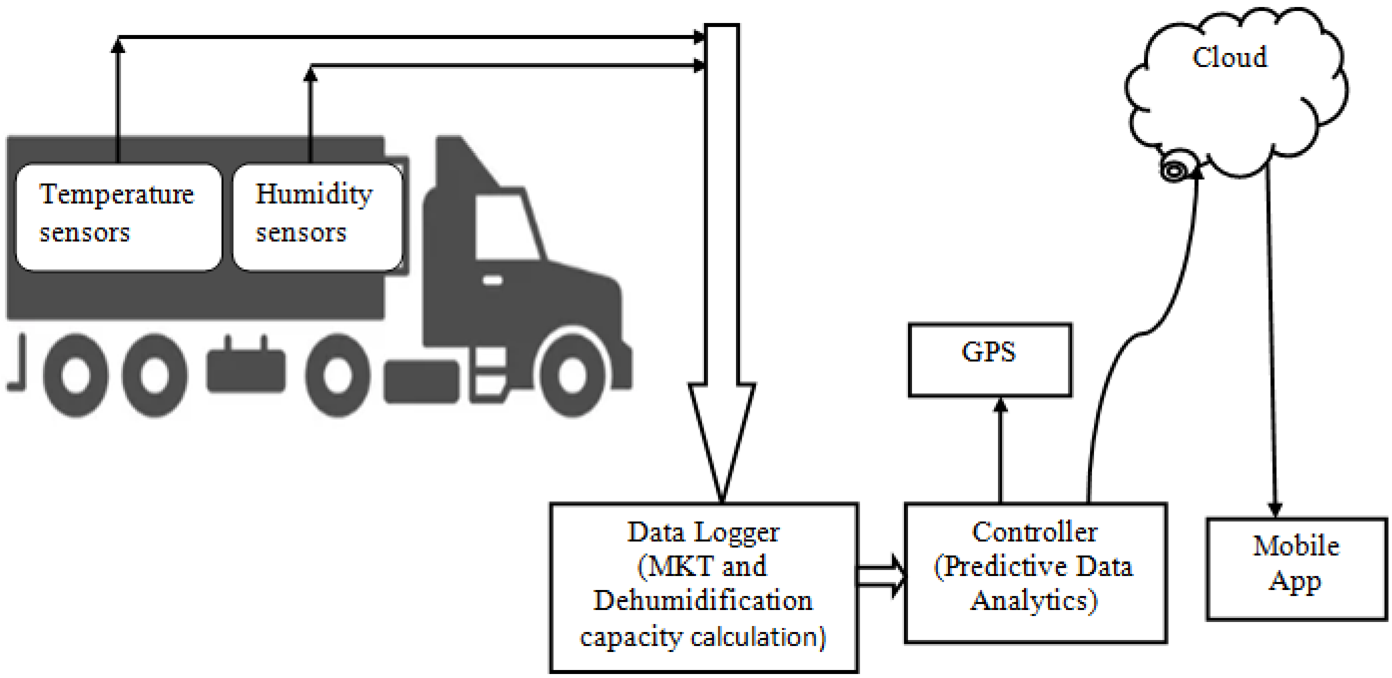

Figure 1

Cold Chain Management System

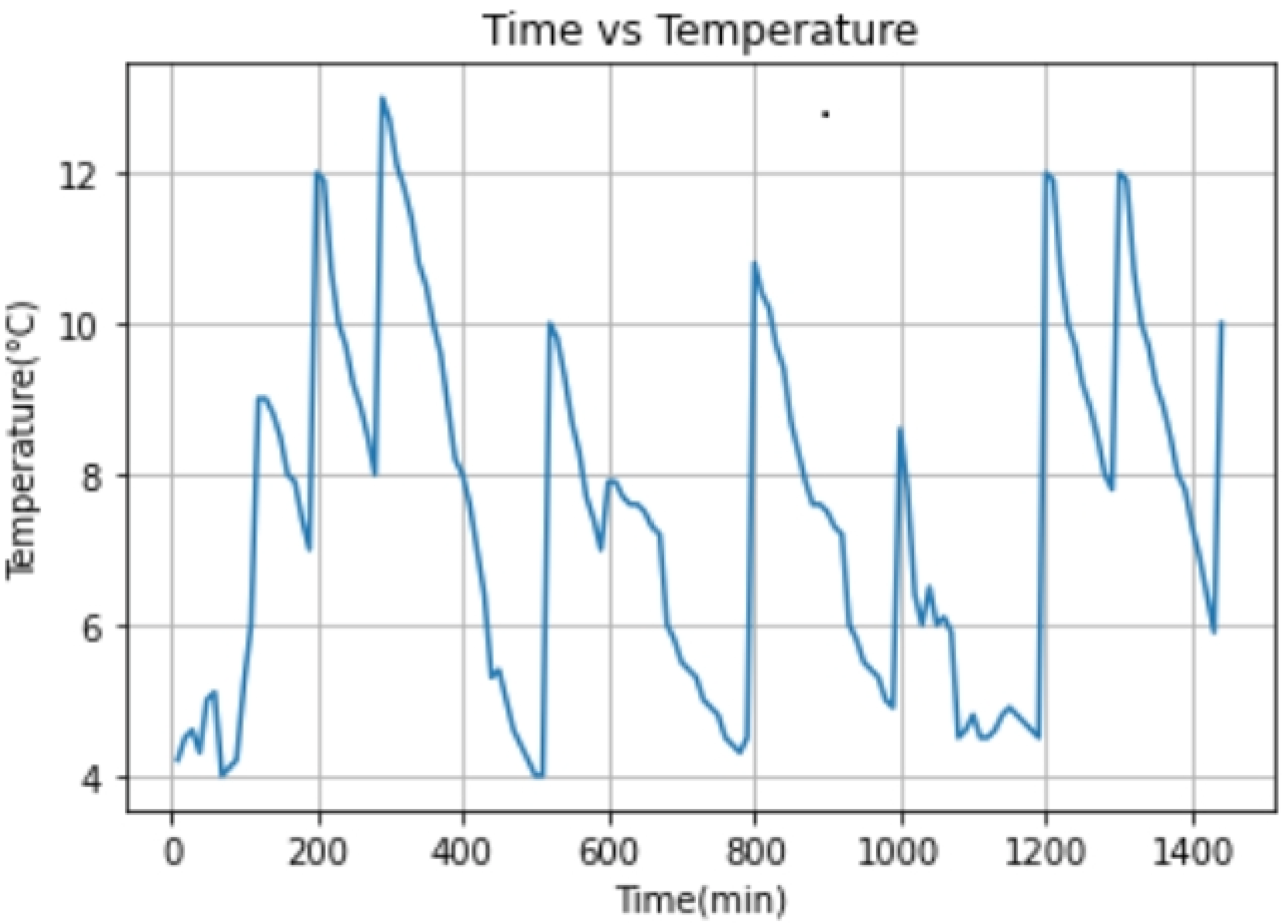

Figure 2

Time Vs. Temperature

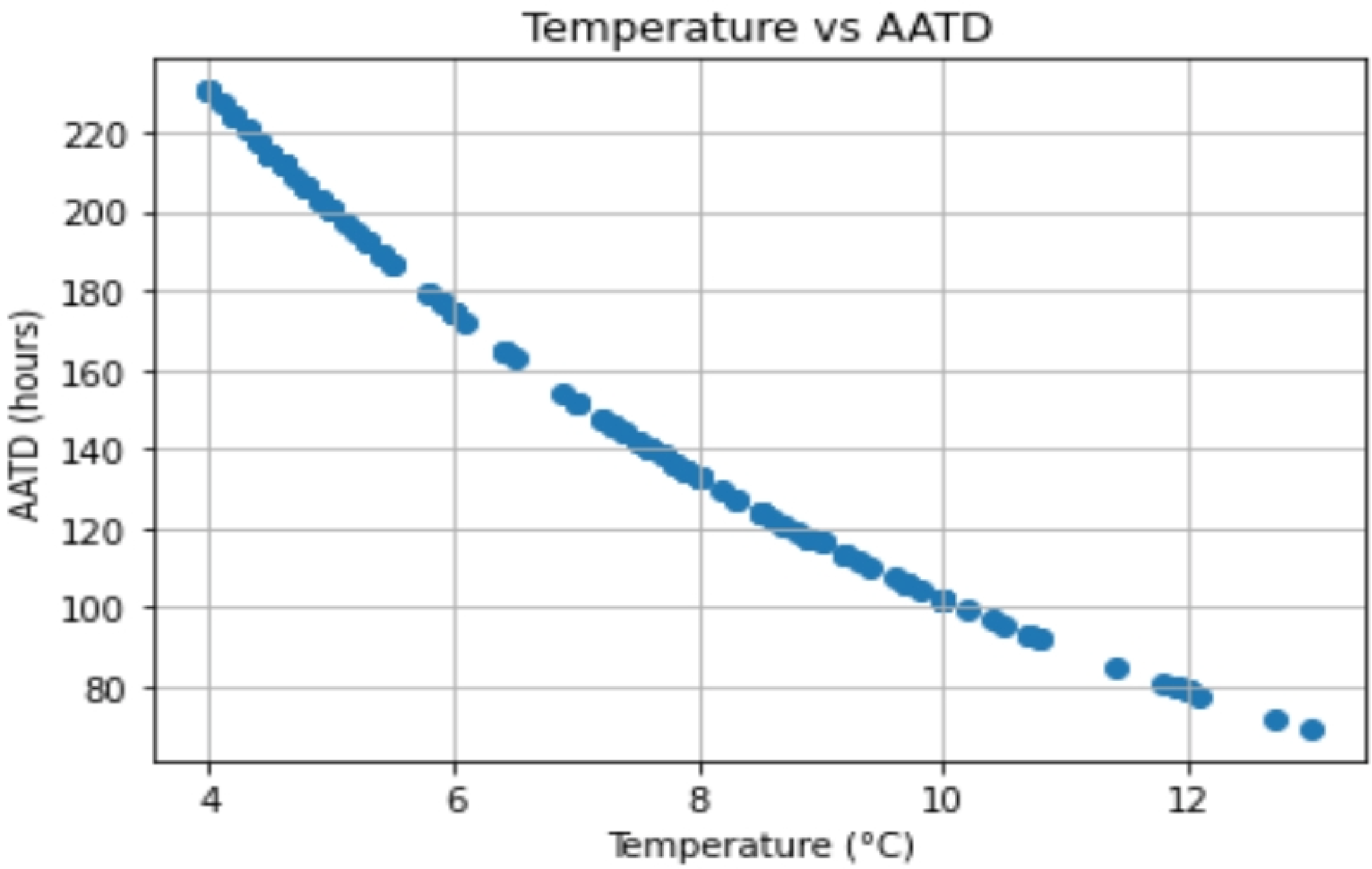

Figure 3

Temperature Vs. AATD

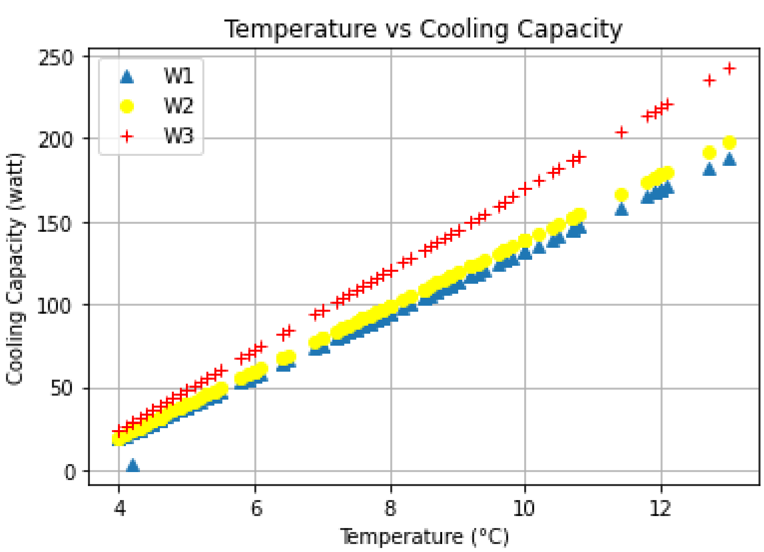

Figure 4

Temperature Vs. Cooling Capacity for Surface Areas S1=26.9 m², S2=28.3 m², S3=34.6 m²

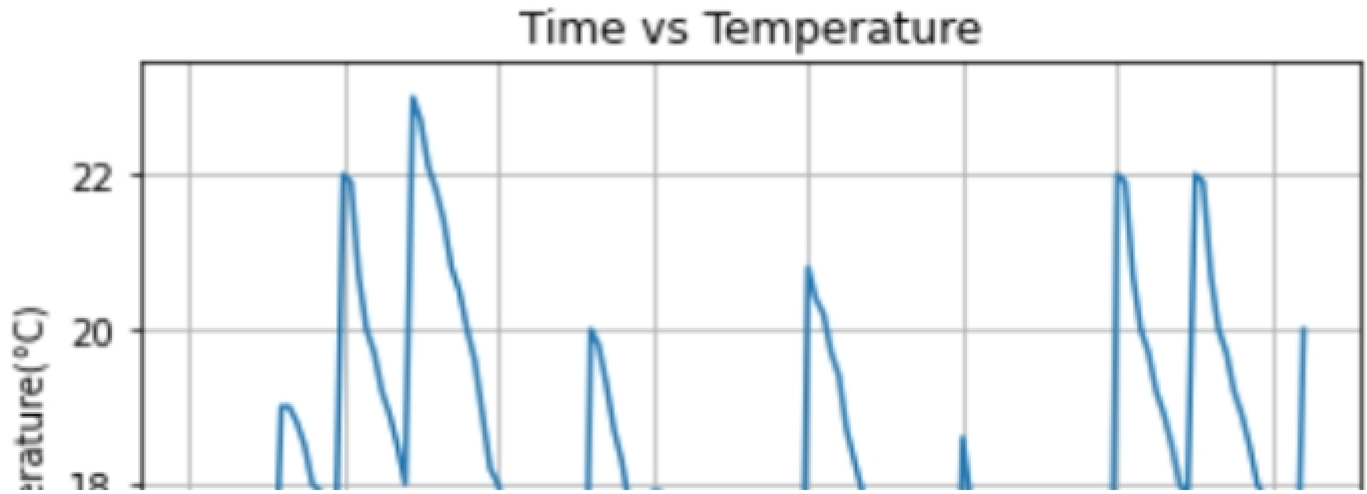

Figure 5

Time Vs. Temperature

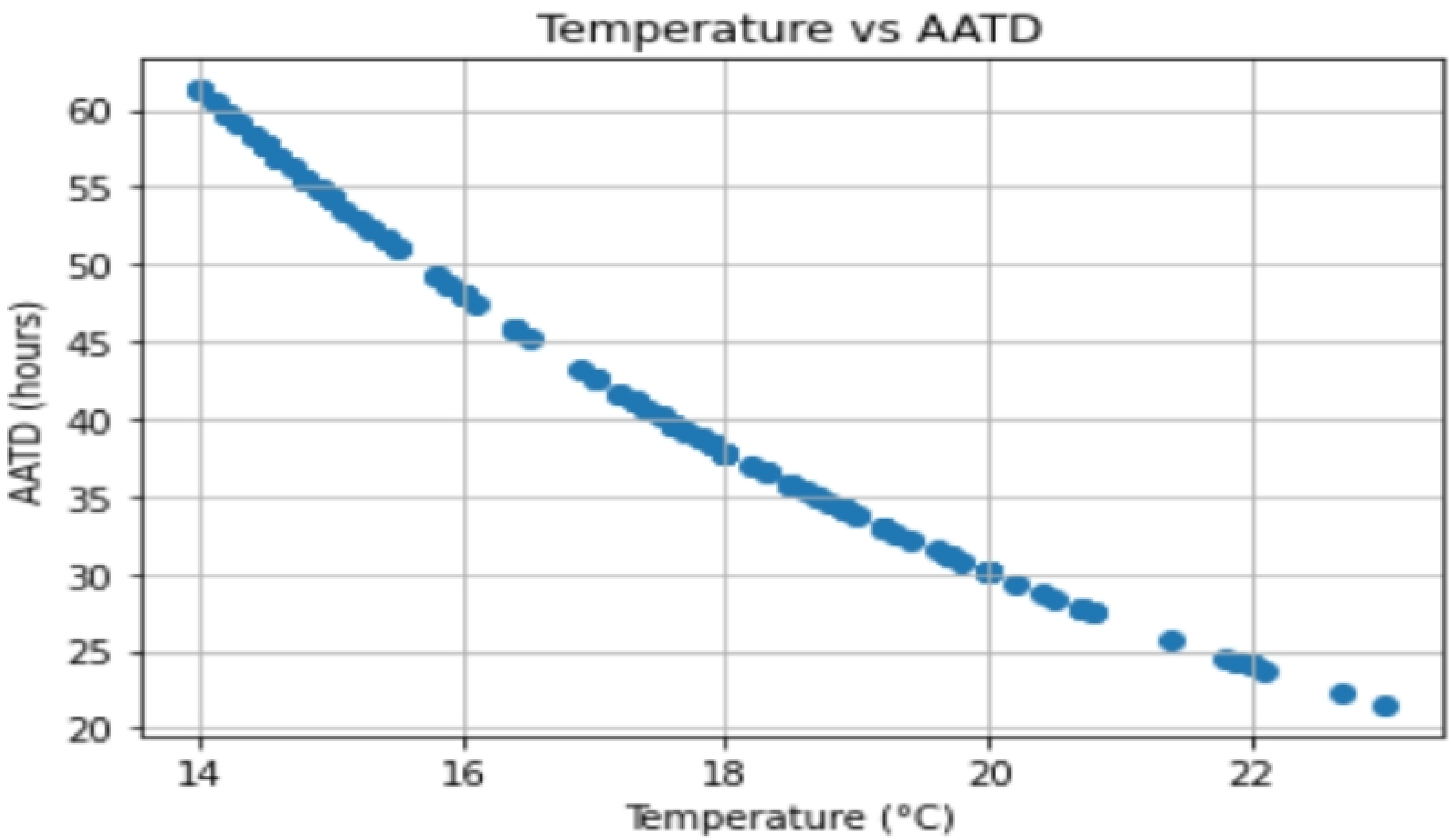

Figure 6

Temperature Vs. AATD

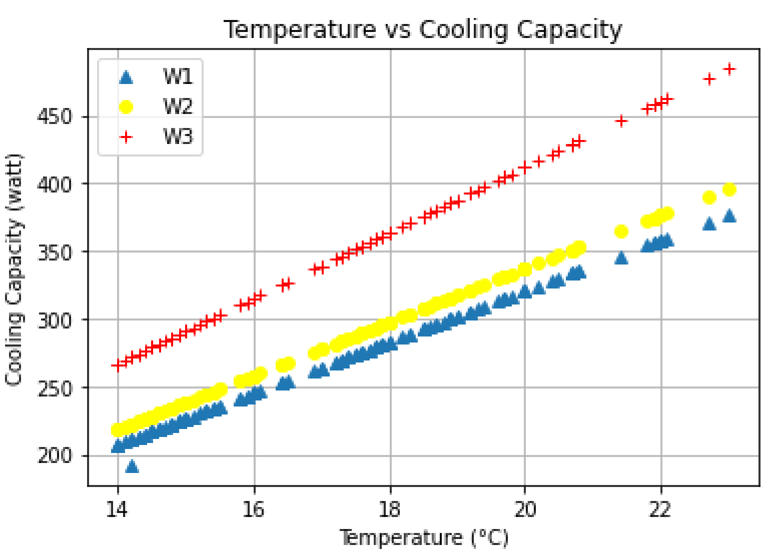

Figure 7

Temperature Vs. Cooling Capacity for Surface Areas S1=26.9 m², S2=28.3 m², S3=34.6 m²

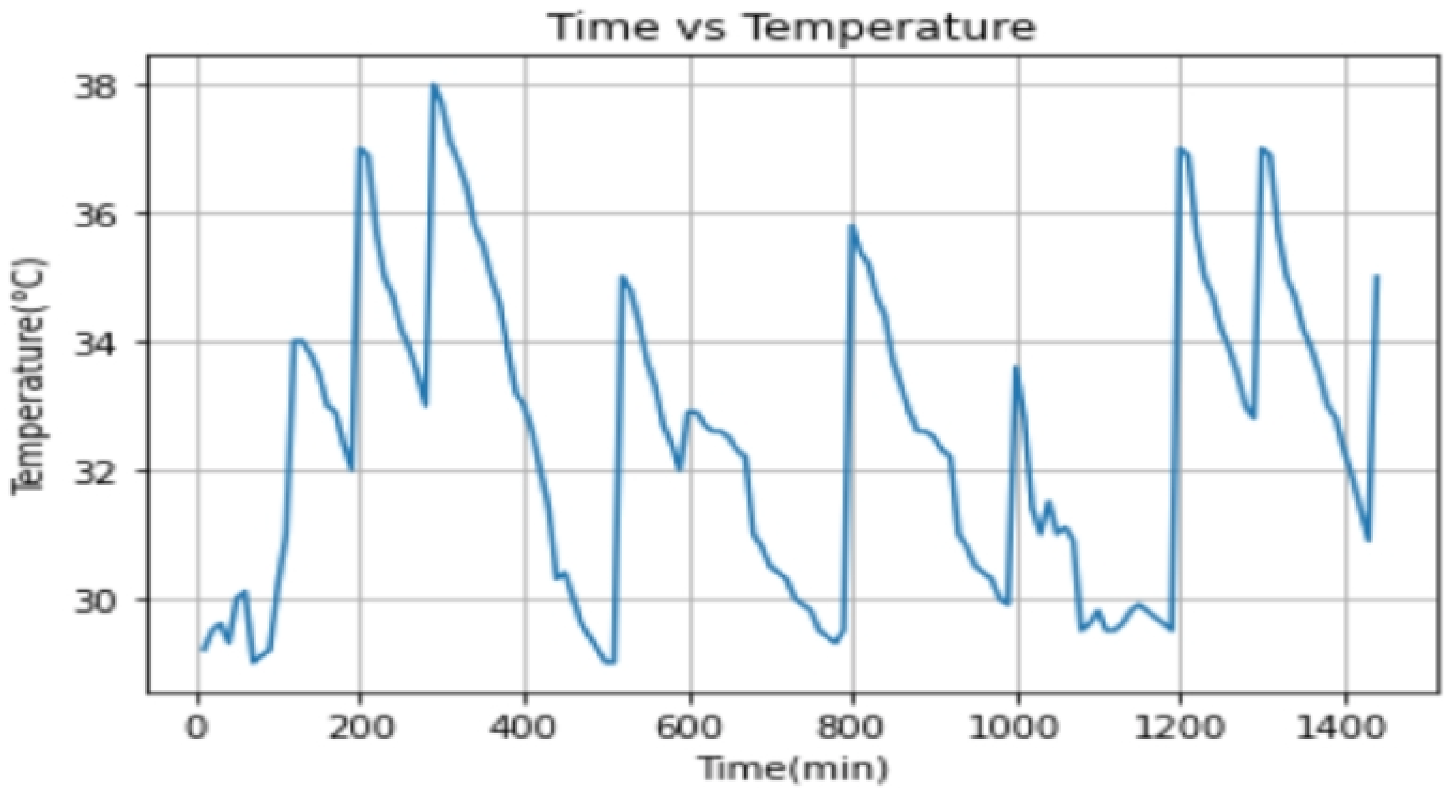

Figure 8

Time Vs. Temperature

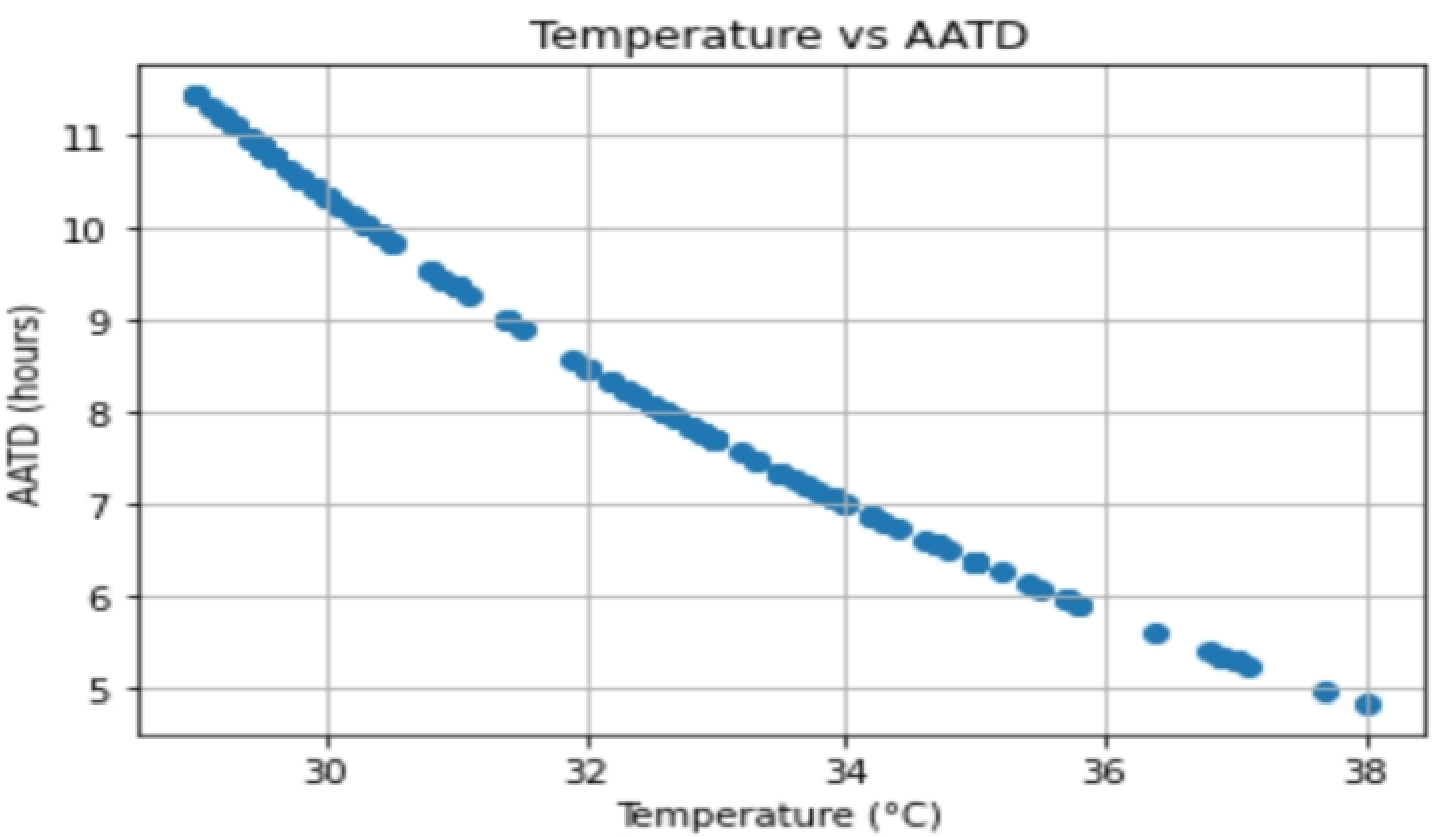

Figure 9

Temperature Vs. AATD

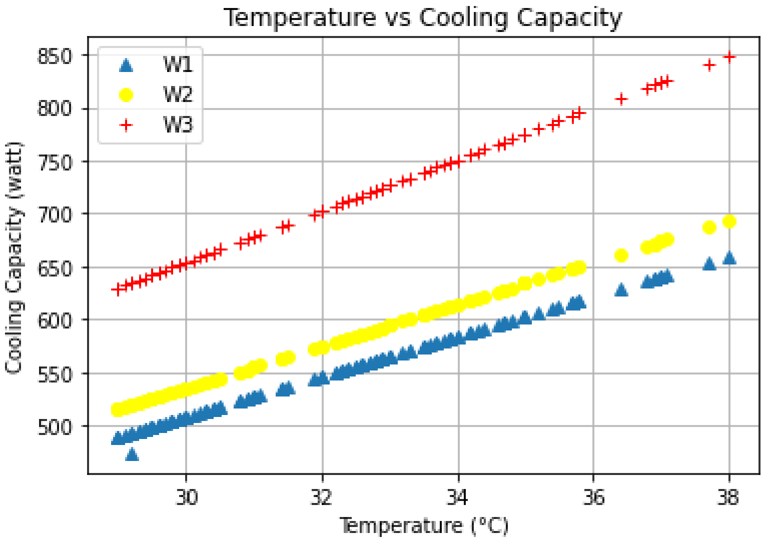

Figure 10

Temperature Vs. Cooling Capacity for Surface Areas S1=26.9 m², S2=28.3 m², S3=34.6 m²