A COMPUTATIONALLY EFFICIENT AND SCALABLE SHELF LIFE ESTIMATION MODEL FOR WIRELESS TEMPERATURE SENSORS IN THE SUPPLY CHAIN

Ismail Uysal[(a)], Jean-Pierre Emond[(b)], Gisele Bennett[(c)]

[(a,b)] College of Technology and Innovation, University of South Florida Polytechnic, Lakeland, FL, USA
[(c)] Georgia Tech Research Institute, Georgia Institute of Technology, Atlanta, GA, USA

[(a)] iuysal@poly.usf.edu, [(b)] jpemond@poly.usf.edu, [(c)] gisele.bennett@gtri.gatech.edu

ABSTRACT
Radio frequency identification (RFID) enabled temperature tracking technologies are used to monitor perishables such as fresh produce and pharmaceuticals during storage and transportation to validate the temperature integrity of the supply chain. With the help of RFID readers, the data stored in the memory of an RFID tag can be up-linked to a computer for further information processing. In this study, we develop a computationally-efficient, quality index based shelf life estimation model which operates on the stored temperature data in an RFID tag's sensor memory to predict the remaining shelf life using a parametric matrix. The advantages of the proposed model over conventional approaches like Arrhenius equation include: multi-component quality analysis, scalability to higher dimensions with additional environmental parameters such as humidity, greater control over the trade-off between accuracy and complexity and finally adaptability to application requirements and sensory device capabilities such as memory capacity and sampling speed.

Keywords: RFID, shelf life estimation, food quality, food safety, temperature estimation

1. INTRODUCTION
The shelf life estimation model discussed in this paper is developed as part of a project which employs an RFID system with handheld readers and temperature tags to estimate the remaining shelf life of army rations to increase food quality and safety. There are multiple approaches to shelf life modeling and estimation for perishable products such as the Arrhenius equation which formulates how the rate of a chemical reaction changes with temperature as shown below:

$$\boxed{k = Ae^{\frac{-E_A}{RT}}}$$

where the rate constant k of a reaction depends on the temperature T, whereas the pre-exponential factor A, the activation energy E_a and the gas constant R do not change with temperature (Petrou et. al. 2002). The coefficients in this equation such as k and E_a depend on the type of product and are determined experimentally by observing the speed of degradation at different

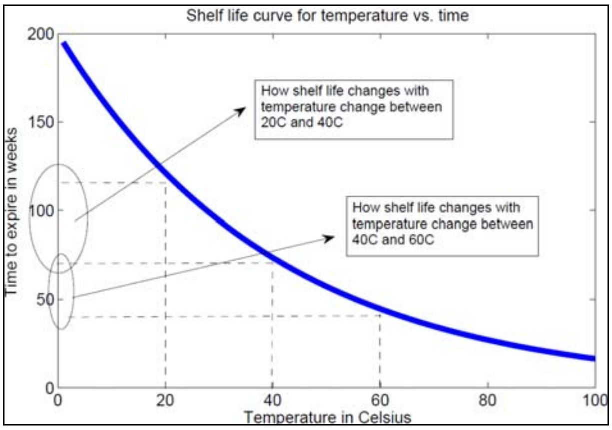

Figure 1: A typical shelf life curve for a product based on Arrhenius equation.

temperatures. Based on such experimental observations and the exponential form factor of Arrhenius equation, a typical shelf life curve which shows the time to expire vs. temperature is shown in figure 1 for the army rations used in this project. At normal temperatures, the army rations have a minimum shelf life of two years as can be observed from the above figure and the time to expire falls with increasing temperature similar to other perishable products. Given the average temperature during a shipment and storage cycle, one can approximate the remaining shelf life on a pallet of army rations by looking at the plot in figure 1.

However, in a typical sensory monitoring application, the tracked environmental variables, such as temperature points, are stored as pairs of value & timestamp instead of a single average temperature value. For example, if the sensory device is sampling the temperature every n minutes, in N minutes of total sampling time there are N/n pairs of temperature & timestamp data points which provide better insight to the temperature distribution within the supply chain. However, in order to utilize such information with higher resolution, unlike Arrhenius model, one needs to utilize more data driven and scalable models which can accommodate the capabilities of the sensory device. In addition, with advance of better sensory devices, other environmental variables, such as humidity can be tracked efficiently and should be used for more accurate shelf life estimation. Finally, today's customer experience oriented approach to perishable supply chain, such as food qualities ranging from taste to color to odor, should be accounted for in a robust model. In this paper we propose a computationally efficient, quality index and parametric matrix based shelf life estimation model which is built open the multiple quality curve approach to perishables (Nunes 2008).

2. SHELF LIFE ESTIMATION MODEL

The quality models used in this project for different items in a package of army rations are the following five qualities: appearance, flavor, odor, texture and overall quality. Each of these quality factors has a quality index (QI) which ranges between 9.0 and 1.0 where 9.0 indicates the highest (initial) quality and 4.0 indicates the lowest acceptable quality. In order to find the QI values, periodic taste panels are performed where different batches of products which are exposed to different temperatures equally distributed within 27°C and 60°C, are sampled and their qualities assessed by trained participants. Through these taste panels, multiple sets of time-temperature data are obtained for each of the five qualities. An example data set is shown in table 1 for a storage temperature of 49°C.

Table 1: Taste panel results for a packaged item from army rations stored at 49°C and sampled at every 2 weeks

Weeks	App.	Aroma	Flavor	Texture	Overall
0	7.9	7.9	8.0	8.0	7.9
2	5.8	6.0	5.8	5.8	5.8
4	4.7	4.9	4.6	4.3	4.4
6	3.8	4.0	3.8	3.6	3.9
8	3.1	3.6	3.3	3.1	3.2
10	2.8	3.3	3.1	3.0	3.0

These results are averaged over all the people who participated in the taste panel and the colored entries show when the QI first drops below the threshold value of 4.0 and the product is declared inconsumable.

2.1. Formulation of Quality Index Change

The QI value of a specific product-quality pair depends on three important factors: the previous QI and the time and the temperature between the last sampling instant and the present. The following equation summarizes the relation between the past and present QI.

$$\boxed{Q_{I_{current}} = Q_{I_{previous}} - f(Q_{I_{previous}}, t, T)}$$

where $Q_{Icurrent}$ and $Q_{Iprevious}$ indicates the current and previous QI values after time t and average temperature T. As shown in the equation, the drop in the QI is a function of the previous QI, time and temperature. Hence the problem of constructing a shelf life model with this approach can be reduced to finding where the current QI drops below the acceptable threshold of 4.0, or in other words, finding the function *f*.

Unlike Arrhenius equation, the function, *f*, needs to be defined and is different for each quality value which requires the use of multiple quality models, or in other

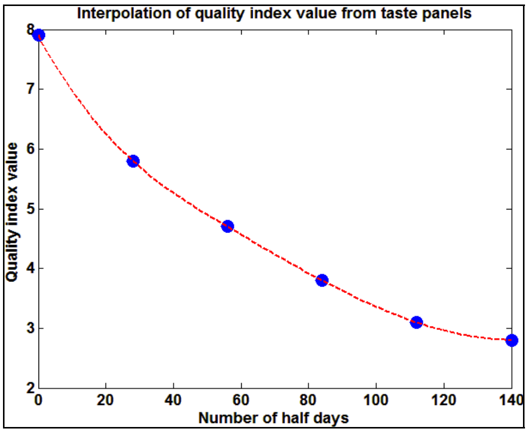

Figure 2: The interpolation of quality index value for the appearance quality of the product in table 1.

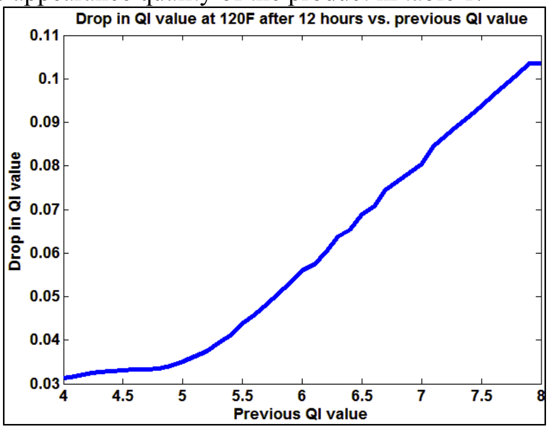

Figure 3: The plot that shows how much QI will drop depending on previous QI value, temperature and time (note 120°F = 49°C)

words, a parametric matrix. For example, for the product in table 1, we only have 6 sampling instants in time which are 2 weeks apart. However, the RFID temperature sensor used in the project samples twice every day. In order to construct a shelf life model which can make full use of this information, the first interpolation will take place in time, as shown in figure 2. The next step is to find how QI changes with time at a specific temperature and previous QI value. Since the time between sensor sampling instants will be fixed for an application (in this case 12 hours) one can use the values in figure 2 to find for each possible QI value between 4.0 and 8.0, how much the QI drop will be after 12 hours at 49°C as shown in figure 3. However, since there are only 4 experimental temperature points, a second 2-dimensional interpolation is performed between the QI drop vs. previous QI value curves for different temperatures. In order to make the algorithm run on a handheld RFID reader such as the one used in the project, this interpolation can be sampled at discrete temperature points (such as every 1°C) to create a set of parametric 2x2 matrices for each quality. Given a previous QI value and temperature, such a matrix provides the corresponding quality drop in the previous equation, thereby serving as the estimation function *f* as shown in figure 4.

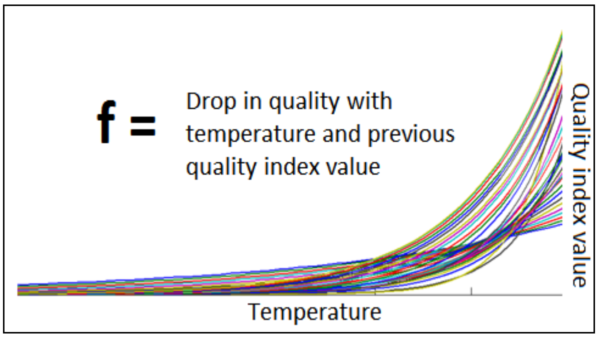

Figure 4: The function, f, which outputs the drop in quality with temperature and previous QI value given initial QI value (as indicated by lines with different colors)

Hence, the proposed model is not only computationally efficient, as it only uses look-up tables for shelf life estimation, but also has complete control over the trade-off between accuracy and performance. In addition it is scalable to other parameters such as humidity and its parametric approach can be modified based on sensory device capabilities and specific requirements of the application.

3. TEMPERATURE ESTIMATION MODEL

Temperature tracking and shelf life estimation of perishable products such as fresh produce or temperature sensitive pharmaceutical drugs during their transportation has been vital to ensure the quality degradation remains acceptable when the items reach their end destination. RFID enabled temperature loggers take this to the next level by adding the capability of wireless data transfer to remotely monitor the temperature inside a shipping container (Opasjumruskit et. al. 2006). Such information would pave the way for intelligent distribution practices such as first-expired-first-out (FEFO) instead of the more commonly used first-in-first-out (FIFO) based on the differences in the temperature profiles witnessed during transportation of individual shipments.

However, due to the dynamics of heating/cooling cycles, it is well known that the temperatures in close vicinity of the products may be different than the temperatures measured inside the shipping container itself (Faghri et. al. 2010). For instance, the temperature inside the container can change more rapidly than the temperature inside a pallet of tightly packed food products. In some cases this might be helpful; such as when the temperature inside the pallet is low and the temperature inside the container increases rapidly. In such a scenario, it will take longer for the pallet temperature to rise to the level of container temperature, which might have a positive impact on the remaining shelf life. However, in the opposite case, even when the temperature inside the container cools down, it will take longer for the pallet temperature to come down as well that will negatively affect the remaining shelf life. In summary, it is crucial to measure the temperature inside the pallet rather than the container to have a more accurate representation of the remaining shelf life.

The limitations of RFID technology, such as reduced performance near metals and liquids might prevent placing RFID temperature tags inside pallets with significant metal and liquid content. One example to this would be First Strike Rations (FSR) as they are shipped and stored in tightly packed pallets where the shipping or storing temperatures can exceed 150-160°F, which results in reduced shelf life. Since the algorithm developed in this paper deals with the estimation of remaining shelf life based on the temperatures measured by RFID temperature loggers during shipment and storage, in order to best monitor the temperature inside the pallet, the trivial solution is to place the temperature tags inside for more accurate measurement. However, this causes serious problems during the interrogation of these tags due to all the metal and liquid content of the rations inside the pallet. Hence, the tags are placed outside the pallet, measuring only the temperature inside the container. One can use this information as an approximation to the actual temperature inside the pallet and calculate remaining shelf life based on this data, however there is a more accurate way of estimating the temperature in close vicinity of the products inside the pallet.

The following study was performed to find the correlation between the temperatures inside and outside a pallet of army rations during heating/cooling of the environment. Five different experiments were carried out where a pallet of army rations was exposed to different heating/cooling cycles. One temperature sensor was placed outside the FSR pallet and two sensors inside the pallet, labeled as *Alpha* and *Prime*. Based on the heating/cooling intervals, the tests can be divided as follows: 6 hours/6 hours, 18 hours/18 hours, 24 hours/24 hours, 2 days/2 days and 4 days/4 days.

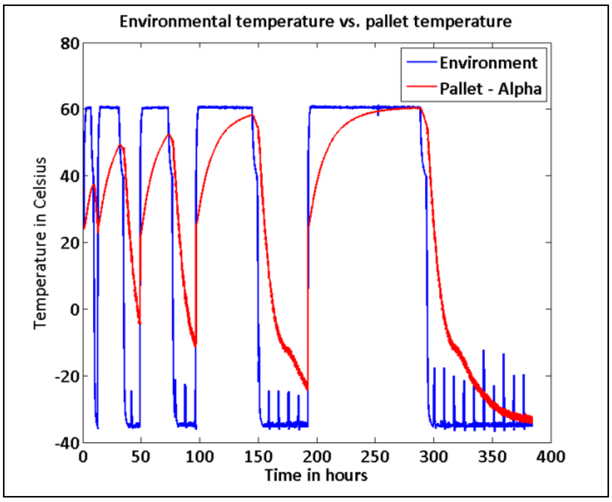

Figure 5: The temperature change inside the pallet at point labeled *Alpha* and how it fluctuates with the change in environmental temperature

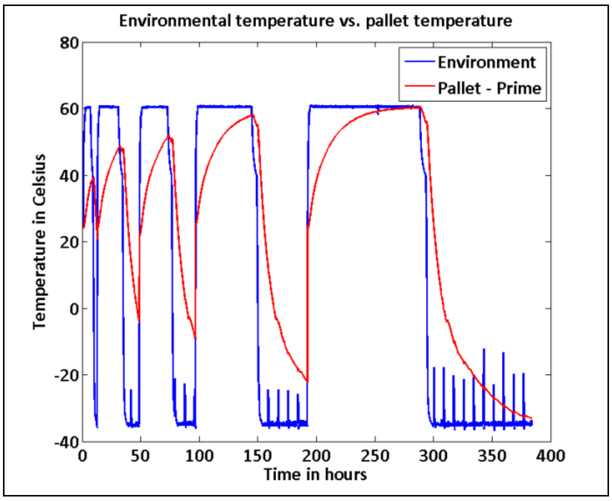

Figure 6: The temperature change inside the pallet at point labeled *Prime* and how it fluctuates with the change in environmental temperature

Figure 5 shows a concatenated plot for the measured temperature levels inside and outside the rations pallet during the entire study for the point labeled *Alpha* inside the pallet. Similarly, figure 6 shows the same plot for the point labeled *Prime*. As expected, the temperatures inside the pallet show a capacitor effect to rapidly changing temperature by slow heating/cooling cycles. In other words, the temperatures rise and decay with a time constant (though slightly different for the two points) that can be determined from these five experiments and can subsequently be modeled to estimate the temperature inside the pallet given the environmental temperature.

In order to better explain this phenomenon, let's take a look at a strikingly similar analogy where the environmental temperature is modeled by the potential difference between the terminals of a voltage source and the pallet temperature is modeled by the potential difference between the terminals of a capacitor as shown in the electronic circuit of figure 7 (Paul 2001).

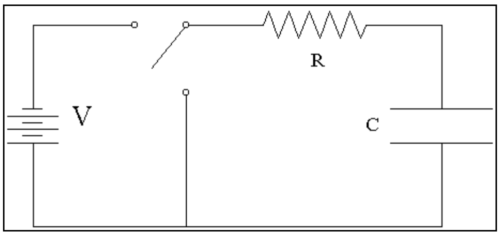

Figure 7: A typical resistor-capacitor circuit to simulate the behavior of the pallet temperature in the presence of changing environmental temperature

In this figure, V represents the environmental temperature and V_c represents the pallet temperature. The relation between the two temperatures can be explained by the following equation:

$$\boxed{V_c = V_c^{initial} + \left(V - V_c^{initial}\right)\left(1 - e^{\frac{-t}{RC}}\right)}$$

where $V_c^{initial}$ is the initial pallet temperature, R is the resistance of the resistor and C is the capacitance of the capacitor. In other words, the pallet temperature will rise or fall with a speed determined by the time constant (RC) and the difference between the temperature of the pallet and the environmental temperature. The bigger the difference the faster temperature will change inside the pallet.

In order to find the time constant empirically, one has to change the potential V and observe how the potential V_c changes with time. Both figures 5 and 6 provide enough information on how to find the time constant for both rising and falling temperatures. If we rearrange the terms in the above equation to find τ (RC), we arrive at the following equation:

$$\boxed{\tau = \frac{-t}{\ln\left(\frac{V - V_c}{V - V_c^{initial}}\right)}}$$

Hence, if one knows the temperature inside the pallet at a given time, t, the initial temperature inside the pallet and the environmental temperature, it becomes trivial to calculate the time constant. Unlike the electronic circuit described above, it is possible to have a different time constant for heating and cooling cycles and the way experiments are designed will allow for separate calculation of the two.

Let's take a look at the last experiment to calculate τ_{rising} for *Alpha* point. In this experiment, the average environmental temperature sits at 60.5°C. If we define t = 0 as the time the pallet temperature started to increase from 24.6°C, we can then choose a 2nd temperature point-time pair to calculate the time constant. For this example, let's look at the last study (4 days/4 days) where it takes t = 76 hours for the pallet temperature to reach 60°C, and this point will be used in the calculations below where T represents temperature and t represents time.

$$T_{pallet}(t = 0) = 24.6C$$

$$T_{environmental} = 60.5C$$

$$T_{pallet}(t = 76\ hours) = 60C$$

Thus;

$$\tau_{rising} = \frac{-76}{\ln\left(\frac{60.5-60}{60.5-24.6}\right)} = 17.8\ hours$$

Similarly, to find $\tau_{falling}$, one only need define two time-temperature points where the pallet temperature slowly approaches the environmental temperature. We choose the same study using a 4 day cooling period to determine the falling time constant.

$$T_{pallet}(t=0) = 60.5C$$

$$T_{environmental} = -35C$$

$$T_{pallet}(t = 67.5\ hours) = -33C$$

$$\tau_{falling} = \frac{-67.5}{\ln\left(\frac{-35-(-33)}{-35-60.5}\right)} = 17.5\ hours$$

Based on these time constants, estimating the temperature inside the pallet can be modeled by the following two equations.

$If\, T_{environmental} > (T-1)_{pallet}$, then...

$$T_{pallet} = (T-1)_{pallet} + \left(T_{environmental} - (T-1)_{pallet}\right)\left(1 - e^{\frac{-t}{\tau_{rising}}}\right)$$

$If\, T_{environmental} < (T-1)_{pallet}$, then...

$$T_{pallet} = (T-1)_{pallet} + \left(T_{environmental} - (T-1)_{pallet}\right)\left(1 - e^{\frac{-t}{\tau_{falling}}}\right)$$

where T_{pallet} is the current estimated pallet temperature and $(T\text{-}1)_{pallet}$ denotes the previously estimated temperature sample.

Remember that this model is only an approximation of the actual temperature inside the pallet as measuring this temperature directly is difficult with RFID technology. In order to gauge the performance of this model, let us compare the model output with the actual measured temperature inside the pallet. Figure 8 shows the estimated pallet temperature against the actual pallet temperature measured by the sensor. As clearly observed from this figure, the estimated temperature is much closer to the pallet temperature than the environmental temperature and thus would be a much better candidate to be the temperature profile used in shelf life calculations.

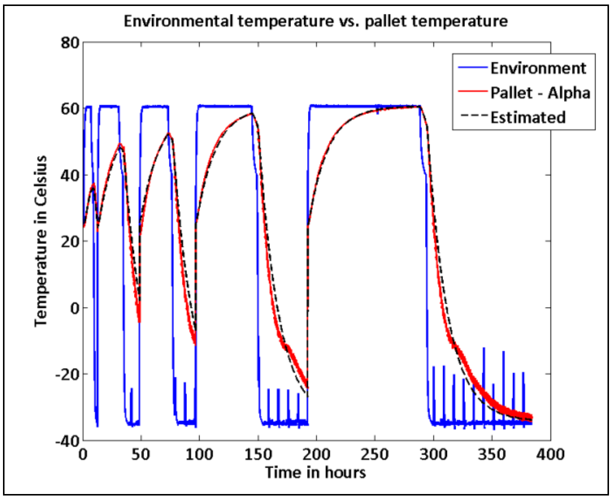

Figure 8. Comparison of environmental temperature, measured pallet temperature and the estimated pallet temperature for *Alpha*

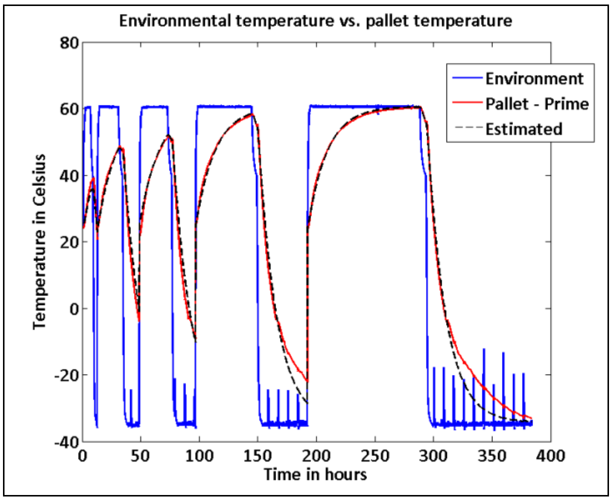

Figure 9. Comparison of environmental temperature, measured pallet temperature and the estimated pallet temperature for *Prime*

In terms of numerical evaluation, the root-mean-square-error and standard deviation between the environmental temperature and the pallet temperature are as follows:

$$RMS(e)_{environmental\text{-}pallet} = 26.2°C$$

$$\sigma_{environmental\text{-}pallet} = 25.1°C$$

In contrast, the mean error and standard deviation between the estimated temperature and the pallet temperature are much lower.

$$RMS(e)_{estimated\text{-}pallet} = 2.6°C$$

$$\sigma_{estimated\text{-}pallet} = 2.5°C$$

Even though these calculations were performed for the point *Alpha*, it's similar for the other point *Prime* as well. Figure 9 shows the estimation results for *Prime.*

$$RMS(e)_{estimated\text{-}pallet} = 2.9°C$$

$$\sigma_{estimated\text{-}pallet} = 2.8°C$$

The slight discrepancy in performance for points *Alpha* and *Prime* can be attributed to the fact that *Prime* shows a different temperature roll-off behavior at subzero temperatures than *Alpha*. This non-uniform behavior cannot be approximated accurately by the single order model. Future work will include piecewise modeling to account for such discrepancies in temperature time constants at different temperature intervals.

To summarize, where one needs to estimate the shelf life of a product based on an RFID tag attached outside the pallet, it is significantly better to estimate the pallet temperature using this model and then use the estimated temperature to calculate the remaining shelf life for much accurate results.

A simple capacitive model, though was shown to be quite effective, can be outperformed by more complex estimation models such neural network or time series estimations. As future work, we will explore these possibilities and more importantly integrate this type of temperature estimation inside the shelf-life model described in this paper for a comprehensive software approach.

4. CONCLUSIONS

In this paper a computationally efficient and scalable shelf life estimation algorithm is described, specifically designed for wireless temperature sensors in the supply chain which lack the computational and storage capabilities of computers. Furthermore, the complexity of the model can be adjusted for a minimal trade-off in accuracy. Considering the physics of how wireless sensors communicate with their base unit, a temperature estimation algorithm is developed to model the changes in pallet temperature with environmental temperature. Our results show a 90% improvement in root-mean-square-error performance between the pallet temperature and estimated pallet temperature when compared to environmental temperatures.

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