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DYNAMIC IDENTIFICATION OF A BEVERAGE COOLER SYSTEM WITH PREDICTION OF TEMPERATURE STABILIZATION TIME FOR ENERGY SAVING

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Abstract. *This paper investigates the reduction of energy consumption in beverage coolers by shutting it down outside the shift hours. In this context, it is important to know the appropriate time instant for turning on the compressor, ensuring to achieve the steady-state temperature right before the next work shift. Therefore, a system identification method is proposed to predict this time instant, using Newton's law of cooling. An experimental investigation was conducted considering a commercial model of beverage cooler under two levels of thermal load variation, loaded with 32 and 64 liters, and with the thermostat adjusted for two distinct levels temperature, moderate cold and maximum cold. The results demonstrated a maximum error of 2.7% in predicting the time to turn on the compressor. The proposed method achieved an electrical energy saving of 5.6% with the refrigerator operating with maximum load and in the maximum cold configuration. However, the method provided 26% of energy savings with maximum load and with the thermostat set to moderate cold. The results were satisfactory, showing the feasibility of the proposed model. There was an effective reduction in energy consumption of beverage cooler without loss of cold sensation at the time of product consumption.*

Keywords: *refrigeration, Newton's law of cooling, least squares, systems modeling, energy saving.*

1. INTRODUCTION

Demand for electricity has been increasing annually due to population growth and improved quality of life, thereby raising the levels of carbon dioxide emissions in the atmosphere, condition that causes global warming and results in environmental impacts due to climate change (Choi et al., 2018) and (Yan et al., 2019). Household refrigerators account for approximately 6% of the worldwide electricity consumption (EIA, 2004). In recent decades, many efforts have been made to reduce consumption in refrigeration systems. Some studies related to energy saving in residential and commercial refrigerators that can be found in the literature are shown at the following.

In Tassou et al. (2010) a review of current cutting-edge technologies and emerging refrigeration technologies that have the potential to reduce environmental impacts on food and beverage refrigeration was assessed. Some studies describe that it is possible to reduce energy consumption by 10% to 20% in a residential refrigerator simply by behavioral changes (Armani and Boscolo, 2013).

In Negrão and Hermes (2011) the authors discuss a methodology for designing home cooling systems. An optimization algorithm was built upon the simulation model to size the condenser and evaporator heat transfer areas, and also the cabinet insulation thickness. A trade-off between minimum cost and minimum power consumption has been achieved, resulting in a configuration that provides 14% energy savings compared to a conventional system used as a benchmark.

A technique for dynamic modulation of voltage excitation angle applied to the compressor of a refrigerator to operate at an optimal energy consumption is presented in Chuang et al. (2017). This technique allowed to reduce energy consumption by 20.48% over a period of one hour, operating with the door closed. No information was reported about the applied thermal load and about the room temperature during the experiments.

In Sonnenrein et al. (2015) was presented an experimental study that evaluates the influence of latent heat storage elements on the condenser temperature of a refrigerator. To determine energy consumption and temperature distribution, a standard wire and tube condenser is encapsulated with different heat storage elements containing water, paraffin or copolymer compound. The results indicate that the application of phase change material (PCM) decreases the condenser temperature. The best result was the use of a copolymer compound, providing up to 10% reduction in energy consumption.

The work in Liu et al. (2011) examines the application of a diffuser tubes (ejectors) prototype in a residential refrigeration system. The addition of two pressurized steam diffuser tubes, one in the suction line and one in the compressor exhaust line, improved the system Coefficient of Performance (COP) and reduced energy consumption. The results showed an 8% energy saving in the prototype compared to the system with conventional ejectors.

Another study, Ekren et al. (2013) assesses the experimental performance of a direct current refrigeration compressor implemented in a 79-liter refrigerator. Variable speed and constant speed operation performances are compared under four different modes of configuration. During compressor operation in “On” mode and variable speed, the improvement in energy efficiency was 10% and COP was increased by 14% when compared to constant speed mode.

To achieve energy savings in the operation of the existing beverage coolers, such as those in the reviewed works, without making substantial changes in their physical and control structure, would be the simplest task to do. It is also known that many beverage coolers have a well-defined operating shift and can be turned off outside that shift to achieve energy savings without compromising equipment performance for its intended purpose: deliver a properly cooled product at the beginning of the work shift. Considering this, this work proposes a solution that aims to allow, at the end of a work shift, the refrigerator to be replenished (with any load volume) and parameterized with the next shift start time. From this, the thermal dynamics of the refrigerator, considering the load inside it, are automatically identified and the time to reach the steady-state temperature is estimated. The compressor is turned off and automatically restarted with the necessary antecedence to cool the load at the desired temperature until the beginning of the next work shift.

2. MODELING AND PARAMETER ESTIMATION OF REFRIGERATION SYSTEM

A mathematical model is called white-box when it is formulated from the laws of physics, gray-box when the use of the knowledge of the laws of physics is combined with statistical data of the system, and black-box when modeling is completely done through statistical data recorded in both observational studies and experiments (Ljung, 1999).

2.1 Modeling by convection heat transfer mode

Once there is a temperature difference between two media or between different regions of the same medium, there will be a heat transfer (Incropera, 2002). Namely, the three heat transfer mechanisms are conduction, convection and radiation. Particularly, convection occurs when there is heat transfer between a surface and a moving fluid. Convection heat transfer is the heat flux that is proportional to the difference between surface and fluid temperatures, T_s and T_∞, respectively, represented by:

$$q"_{conv} = h_c(T_s - T_\infty) \tag{1}$$

characterized by the convection heat transfer coefficient h_c (Incropera, 2002).

The convection heat transfer mode gives rise to the equation known as Newton's law of cooling and states that the temperature of a body's surface varies at a rate proportional to the difference between its temperature and the surrounding fluid temperature, called room temperature (Chapra and Canale, 2010) and (Kreith et al., 2011). The expression representing this law is an ordinary differential equation (ODE):

$$dT(t)/dt = \bar{k}[T(t) - T_m] \tag{2}$$

where T is the surface temperature of a body [ºC], T_m is the fluid medium temperature [ºC], t is the elapsed time [minute] and $\bar{k}$ is the proportionality constant [minute].

2.2 Parameter estimation by least squares method

A linearly interpolated point y_i, from observations x_{ij}, where $_i$ is the index of the line and $_j$ is the index of the column of this matrix, represented by:

$$\mathbf{y}_i = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 x_{i1} + \boldsymbol{\beta}_2 x_{i2} + \ldots + \boldsymbol{\beta}_n x_{in} + \boldsymbol{\varepsilon}_i \tag{3}$$

In Equation (3) β represents the unknown parameter and ε represents the residual error. The least squares (LS) method consists of finding the values of β_J in Eq. (3) such that the sum of the squares of the errors ε_i is minimized. Therefore:

$$\mathbf{L} = \sum_{i=1}^{N} \left(\mathbf{y}_i - \boldsymbol{\beta}_0 - \sum_{j=1}^{N} \boldsymbol{\beta}_j x_{ij} \right)^2 \tag{4}$$

where L in Equation (4) is defined as the least squares function (Montgomery, 2005).

3. PROPOSED METHOD

This section presents the proposed method for the dynamic identification of the plant and forecast of the compressor activation time.

3.1 Instrumentation and data acquisition

The equipment used in the experiment is a commercial display beverage cooler with a double-glazed door, that has an electromechanical thermostat as a temperature control element. This cooler works on the principle of vapor compression, and relevant technical information of the equipment are: internal volume of 0.3 m³; R134a refrigerant (mass of 0.19 kg); and nominal power of 217 W.

In order to carry out the experimental tests and data acquisition required to identify the dynamic of the system a test structure was assembled as shown in Fig. 1. The beverage used in the experiments was drinking water packaged in polyethylene terephthalate (PET) bottles, 2 liters each. The cooler was installed in a temperature-controlled room, whose temperature (T2) was maintained at 22 ± 1 °C and the relative humidity in the range of 65% ± 10%. It characterizes a Climate Class 2 test room, as recommended by ISO 23953-2: 2015 Refrigerated display cabinets - Part 2: Classification, requirements and test conditions (BSI EN ISO 23953-2, 2015).

The electromechanical thermostat of the equipment has a temperature sensor (T3 - T_{evap}) attached capillary tube fixed with clamp on the evaporator plate surface. The thermostat selector is used to adjust the average temperature of the evaporator plate according to the adjustment position chosen by the user. The considered adjustment positions of the thermostat temperature selector are two, position 1 - moderate cold, with minimum evaporator plate temperature (T_m) of -2 °C, and position 4 - maximum cold, with T_m set to -12 °C. The accuracy of the sensors used for temperature, voltage and current measurements are in accordance with ISO 23953-2: 2015. When the minimum temperature (T_m) is reached, the compressor goes to shutdown mode, momentarily ceasing the refrigeration cycle.

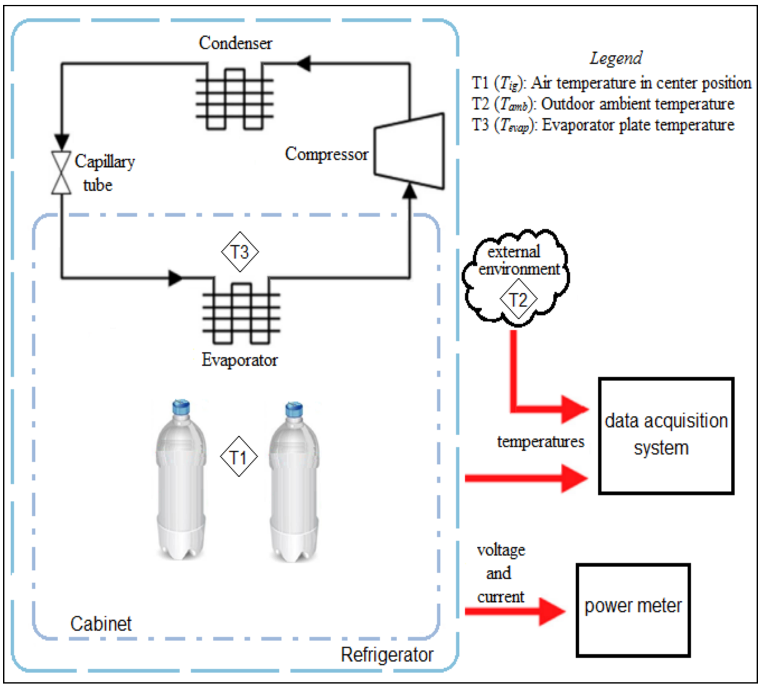


Figure 1. Data acquisition architecture.

3.2 System identification procedures and steady-state time prediction

The cooling system under study has a typical internal air temperature and electrical power profiles that are common to beverage refrigeration equipment operated by vapor compression principle. This kind of cooler usually work with electromechanical thermostat temperature control, as the one considered in this study. In order to identify the heat transfer in the refrigerator it is essential to define the relevant points of the time / temperature curve. Fig. 2 illustrates the typical internal temperature behavior of a full-loaded refrigerator, operating with closed door and set in position 4, without disturbances.

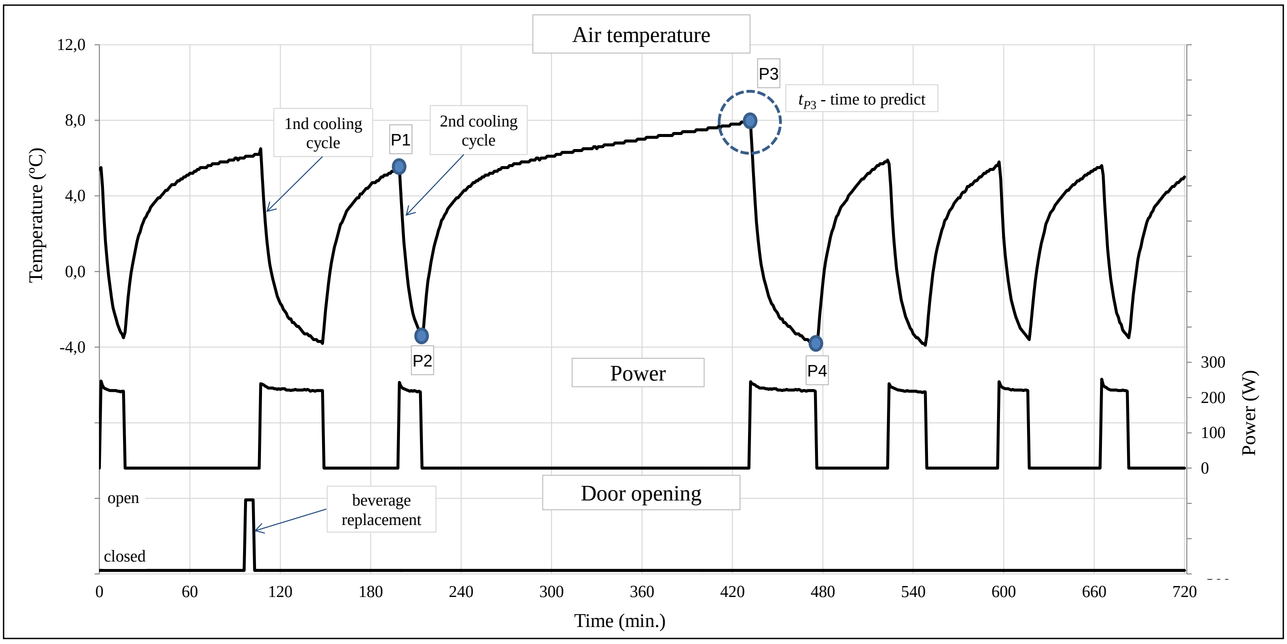


Figure 2. Temperature and power profiles of the refrigerator in discontinuous operation

Point P1 represents the beginning of the second cooling cycle after the door has been opened for a half-volume replacement and before the compressor is shut down. At this time the statistical recording of the *t* and T_{ig} variables will begin, which will dynamically identify the cooling system. Point P2 represents the (forced) shutdown of the compressor in order to save energy and also the end of data collection necessary for the system identification. Point P3 represents the (automatic) reclosing instant of the refrigerator compressor. Point P4 represents the time when the compressor completed the first post-shutdown cooling cycle and reached the target internal temperature required for the start of the new work shift.

The time point *t* of P3 (*tP*3) determines the moment where the compressor automatically turns on. The prediction task aims to determine the location of the point P3 on the heating curve temporal axis. This is accomplished through the analytical resolution of the model such that successive approximations of the cooling curve achieve point P4 with the smallest possible time and temperature error.

3.3 Gray-box modeling method applying Newton's law of cooling

In this section is applied the mathematical modeling of the thermal transfer of the cooling system, using Eq. (2). The value of the proportionality constant $\bar{k}$ influences the rate of variation of temperature in the refrigerator, being dependent on several factors, such as the external ambient temperature, the thermal insulation level of the refrigerator, the volume and the temperature of the beverage inside the cabinet and the adjustment position itself of the thermostat temperature selector.

The temperature variation rate problem presents an analytical solution using the variable separation technique. ODE's general solution in Eq. (2) results in:

$$T(t) = T_m + Ce^{-\bar{k}t} \tag{5}$$

ODE's resolution is bounded to certain initial conditions. Knowing that the initial body temperature at time zero is $T(0) = T_0$, then substituting $t = 0$ in Eq. (5), leads to the value of the constant C:

$$C = T_0 - T_m \tag{6}$$

Substituting the Equation (6) into Eq. (5) results in the general equation that determines the temperature of a body at any time point, where T_0 is the initial body temperature at time zero:

$$T(t) = T_m + (T_0 - T_m)\, e^{-\bar{k}t} \tag{7}$$

To perform gray-box modeling by Newton's law of cooling requires estimation of its unknown parameters, $\bar{k}$ and *C*, which can be conveniently done by linear regression.

Although the least squares technique usually uses linear functions and polynomial approximation functions, depending on the need for application, other functions can be used, such as Eq. (5). In this case, the temperature in the sensor located inside the cabinet at any time is determined by an exponential function, which is therefore nonlinear and must be linearized to allow the estimation of its parameters by the LSM. Applying the logarithm on both sides of Eq. (5) and rearranging the equation, one obtains:

$$ln[T(t) - T_m] = lnC - \bar{k}t \tag{8}$$

In Equation (8), making $ln[T(t) - T_m] = \hat{y}_i$, $\bar{k} = \beta_1$ and $lnC = \beta_2$ leads to:

$$\hat{y}_i = \beta_1 t_i + \beta_2 \tag{9}$$

now, following the LSM procedure, it is possible to obtain the linear function parameters with the appropriate adaption of the terms.

Assuming that LSM consists of minimizing the sum of the quadratic difference between the actual values of the dependent variable y_i and their respective estimated values $\hat{y}_i$, the unknown parameters of the linear approximation function can be determined as follows:

$$e_L = min_{\hat{y}} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{10}$$

where e_L is the minimal quadratic error, *N* is the total amount of observations and $\hat{y}_i$ is the estimated value of the dependent variable. Replacing Eq. (9) in Eq. (10), the resulting optimization problem is:

$$e_L = min_{\beta_1,\beta_2} \sum_{i=1}^{N} (y_i - \beta_1 t_i - \beta_2)^2 \tag{11}$$

By the derivative of the Eq. (11) in relation to β_1 and β_2 and considering that in minimization the partial derivatives are null, we have:

$$\partial e_L/\partial\beta_1 = 0 \quad and \quad \partial e_L/\partial\beta_2 = 0 \tag{12}$$

Considering the solution of the partial derivatives of the errors as functions of β_1 and β_2, and isolating these unknown terms, we have:

$$\beta_1 = \left(N\sum_{i=1}^{N} t_i y_i - \sum_{i=1}^{N} y_i \sum_{i=1}^{N} t_i\right) \Bigg/ \left[N\sum_{i=1}^{N} t_i^2 - \left(\sum_{i=1}^{N} t_i\right)^2\right] \tag{13a}$$

$$\beta_2 = \left(\sum_{i=1}^{N} t_i y_i \sum_{i=1}^{N} t_i - \sum_{i=1}^{N} y_i \sum_{i=1}^{N} t_i^2\right) \Bigg/ \left[\left(\sum_{i=1}^{N} t_i\right)^2 - N\sum_{i=1}^{N} t_i^2\right] \tag{13b}$$

This allows the determination of the parameters $\beta 1$ and $\beta 2$ as functions of t_i and y_i, of the time (*t*) and of the internal cabinet temperature (T_{ig}), dynamically measured.

Predicting the time instant of point P3 is critical for setting the compressor reclosing time to ensure that the beverage reaches the ideal temperature at the beginning of the next work shift. For this purpose, the algorithm that estimates the location of the point P3 at the heating curve is proposed, taking into account the reading of the initial time (t_{P1}) and the value of programmed final time P4 (t_{P4}) for the beverage to be cold.

The estimation algorithm is divided into two parts. In the first, the refrigeration system is identified by estimating parameters $\bar{k}$ and *C*, using Eq. (5). Using these two variables, it is possible to determine parameters β_1 and β_2, using Eq. (13a) and Eq. (13b). In the second step of the algorithm, time (*t*) is predicted in P3. Successive approximations are made, using equation (5) with the identified parameters β_1 and β_2, aiming at the determination of T (*t*) that will guarantee that ($t + t_{P1} - t_{P4}$) is approximately zero. In this condition, T_m depends on the adjustment position chosen by the user, as shown in Tab. 1.

Table 1. Experiment factor level values

Factors	Level	
	-1 (low)	**1 (high)**
a – beverage volume	32 liters	64 liters (full load)
b – position adjustment on thermostat selector	1 (moderate cold)	4 (maximum cold)
c – shutdown time off work shift	0 hours (continuous)	≥ 8 hours off

The algorithm uses the data measured between points P2 and P3. These data are used to identify the $\bar{k}$ and C parameters of the refrigeration model. Information about the time (*t*), internal temperature of the cabinet (T_{ig}), voltage and electric current of the compressor are recorded every minute. At the same time, the cooling curves are estimated, using Eq. (5) until the final stop condition is found. After that, the time prediction process in P3 is completed.

4. RESULTS AND DISCUSSION

In this work, the objective of the experimental investigation is to study the influence and combined effect of the following three factors on the energy consumption of the beverage cooler: (a) the volume of beverages; (b) the position of the thermostat selector; and (c) the off-work shift length. The values -1 (low) and 1 (high) assumed for each factor in the experiments are shown in Tab. 1.

To carry out the experimental investigation it was adopted a factorial design tool, with 3 factors and 2 levels per factor. Thus, the total number of runs results in 8, with 2 replicates per run, totaling 16 samples.

The data observed in the real process are compared with the output data of the proposed models, verifying the Root-Mean-Square Error (RMSE), analogous to the standard deviation, used to measure the quality of the model fitting through:

$$RMSE = \sqrt{(1/N)\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{14}$$

where y_i is the output response variable observed in the process and $\hat{y}_i$ is the estimated or predicted value of y_i.

The R^2 coefficient is used to indicate the explanation of the dependent variable by the regressors present in the model:

$$R^2 = 1 - \left[\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \Big/ \sum_{i=1}^{N}(y_i - \bar{y})^2\right] \tag{15}$$

where $\bar{y}$ is the average of the observations of *y*.

4.1 Identification of system model parameters

To carry out the experimental investigation of parameter identification, the refrigerator was filled with 50% of the beverage volume at room temperature (22 ºC) and the rest of the beverage was already refrigerated inside the cabinet. The door was closed and the equipment was operating for two complete cooling cycles. The temperatures observed in the second refrigeration cycle (P1 - P2) shown in Fig. 2 were used to obtain the models.

The experiments were arranged so that factors a, b and c were grouped into 4 test groups. The measurement was performed by 24 hours for each sample.

The obtained models become monovariable because they use only the time variable (*t*) to calculate the internal air temperature (*T*), considering that T_m depends on the adjustment position chosen by the user in Tab. 1. As an example, in group 1 composed by samples 5 and 14, the factors a, b and c, were set to level 1, i.e., the beverage volume at 64 liters (maximum load), the thermostat setting position at 4 (maximum cold) and off-shift time at 8 hours. The curves of the experiments 5 and 14 are shown in Fig. 3, which illustrate the behavior of internal air temperature (T1) as a function of time (*t*), generating the curve P1 → P2.

The temperature at point P2, seen in Figs. 3,4, 5 and 6, is the measurement of the air temperature inside the cabinet (T1 or T_{ig}) prior to the compressor shutdown and varies depending on the beverage amount and the thermostat setting position, being different from the average evaporator plate temperature (T4 or T_{evap}).

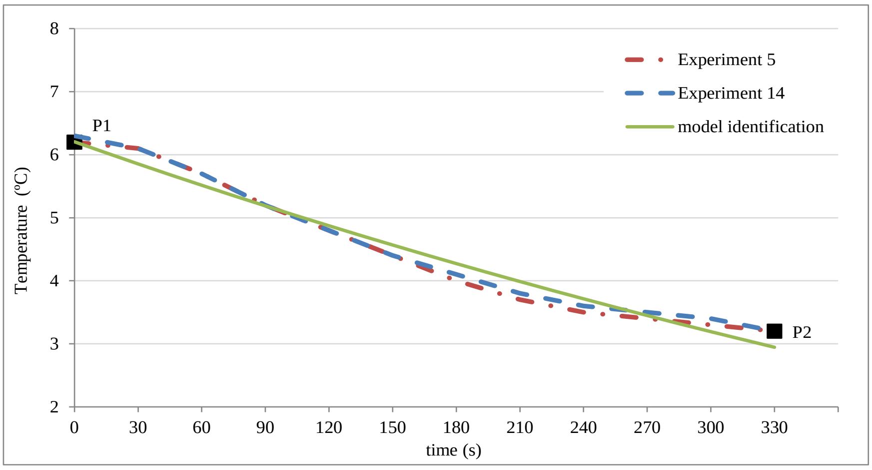


Figure 3. Grouping 1- Temperatures (T1) on curve P1→P2

Fig. 4 shows the curves of the experiments 6 and 8 of group 2, which shows the behavior of the internal air temperature (T1) as a function of time (*t*). The levels of factors a, b and c in this grouping were adjusted to 1, -1 and 1, respectively.

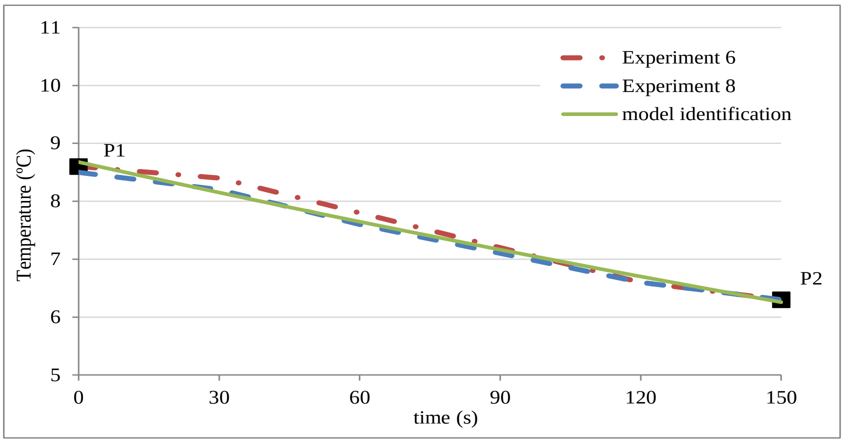
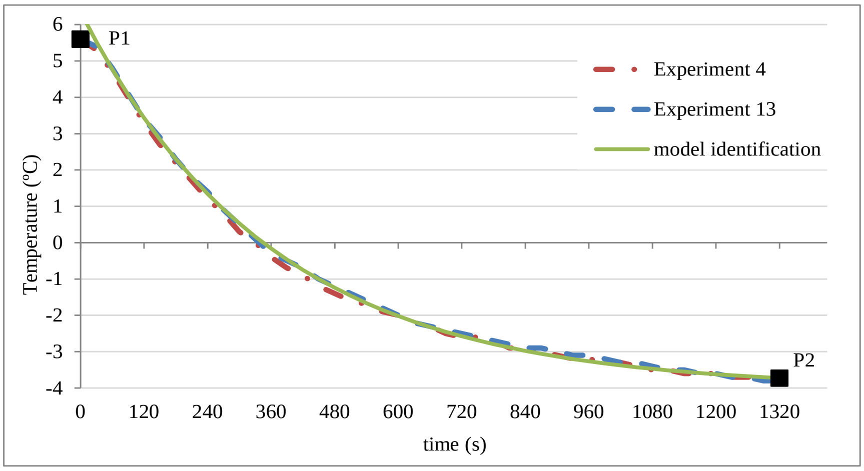


Figure 4. Grouping 2- Temperatures (T1) on curve P1→P2

The curves of experiments 4 and 13 of cluster 3 shown in Fig. 5 illustrate the behavior of the internal air temperature (T1) as a function of time (*t*). The levels of factors a, b and c in this grouping were adjusted to -1, 1 and 1.



c

Figure 5. Grouping 3- Temperatures (T1) on curve P1→P2

The last sequence of the blocks shows the curves of experiments 3 and 11 of group 4 according to Fig. 6. The levels of factors a, b and c in this grouping were adjusted to -1, -1 and 1.

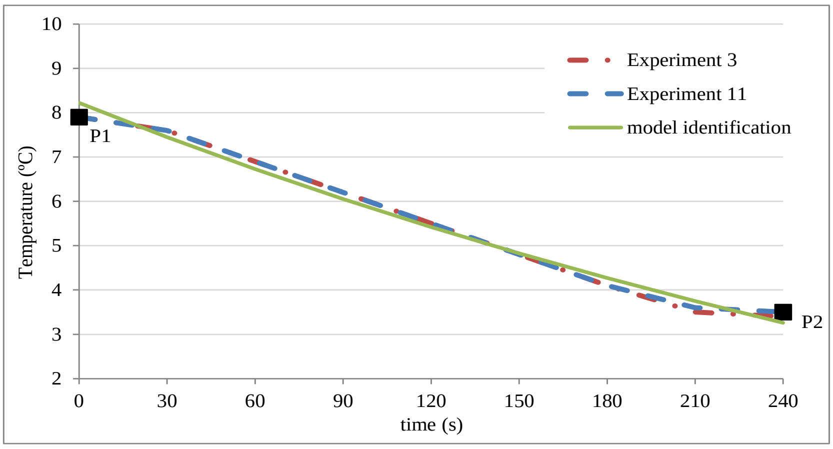


Figure 6. Grouping 4 – Temperatures (T1) on curve P1→P2

Table 2 provides a summary of the identified parameters and the statistical information of each model, separated by groupings. The results show that the mean RMSE was 0.1472 with a standard deviation of 0.0381 and the mean R² was 0.986 with a standard deviation of 0.010.

Table 2. Summary of parameter identification and model statistics

Sample	Grouping	Factor levels			$\bar{k}$	C	N	RMSE	R^2
		a	**b**	**c**					
5 14	1	1	1	1	0.0354 0.0346	10.5626 10.5746	12	0.1729	0.973
6 8	2	1	-1	1	0.0437 0.0410	13.3446 13.1058	6	0.0960	0.986
4 13	3	-1	1	1	0.0826 0.0827	11.0137 11.4596	45	0.1406	0.997
3 11	4	-1	-1	1	0.0658 0.0643	13.0738 13.0109	9	0.1794	0.987
						averages standard deviation		0.1472 0.0381	0.986 0.010

The parameters $\bar{k}$ and C of Table 2 were identified dynamically and will be used by the prediction algorithm. Subsequently, successive calculations of T(t) in equation (2) until finding the ideal time of P3 (t_{P3}) which determines the automatic restart of the compressor, as detailed in the next section.

4.2 Prediction of time to restart the compressor

Prior to beginning the experimental investigation of the prediction step, the refrigerator had already been replenished and was operating under the conditions described in Section 4.1, with the thermostat adjustment position and beverage volume as previously defined, maintaining the instrumentation and procedure structure and acquisition of the data described in Section 3.1. By applying the identified values of $\bar{k}$ and C, according to Section 4.1, the prediction algorithm performed the successive approximations of time in P4 (t_{P4}) until it found the ideal time of P3 (t_{P3}) that determines automatic reclosing of the compressor.

For all prediction tests, the level of factor c - shutdown time outside the work shift was set to 1. Fig. 7 shows the time and temperature profiles of experiments 3 and 6 that compose groupings 4 and 2, respectively. In experiment 3 the levels of factors a and b were adjusted by -1 and -1, respectively. In experiment 6, factors a and b were adjusted to 1 and -1. The graphs in Fig. 7 and Fig. 8 illustrate the observed internal air temperature curves T_{ig} and the points of the internal air temperature prediction model curves generated by the $T(t)$ function in both experiments, generating the prediction curves between points P3 and P4.

In experiment 3, illustrated in Fig. 7, the reclosing time of the measured t_{P3} compressor in the test was 499 minutes and the t_{P3} time predicted by the successive approximation algorithm was 498 minutes. This 1 minute of difference means an error of 0.2% over the total time interval of 8 hours and 19 minutes until the compressor was turned off.

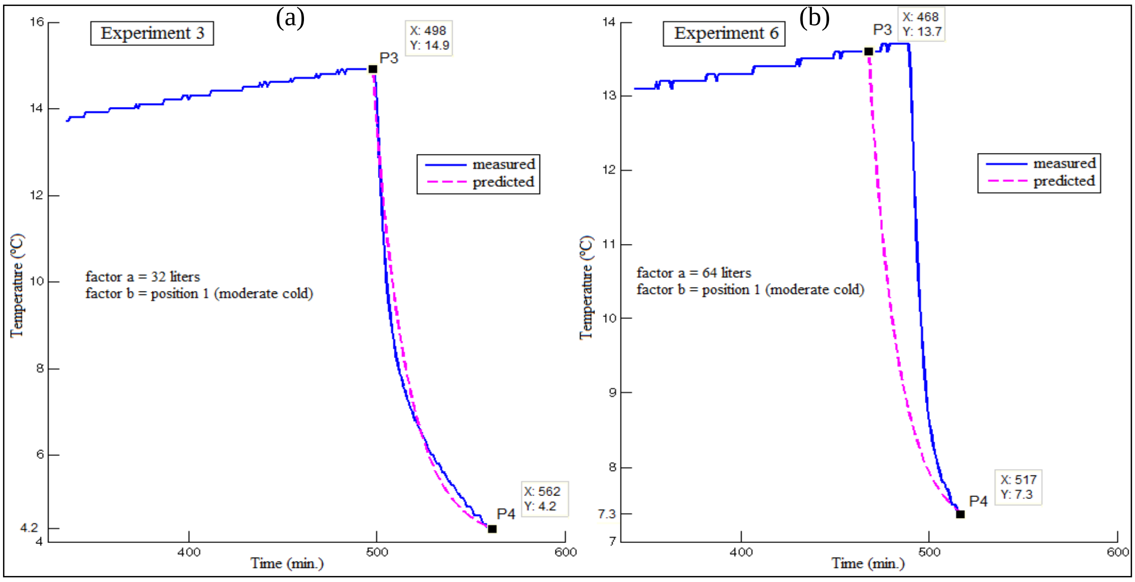


Figure 7. P3 time prediction: a) experiment 3 of group 4, b) experiment 6 of group 2.

In experiment 6, the reclosing time of the t_{P3} compressor measured in the test was 489 minutes and the t_{P3} time predicted by the successive approximation algorithm was 468 minutes. This difference of 21 minutes means an error of 4.3% over the total time period of 8 hours and 9 minutes until the compressor was turned off.

The graphs in Fig. 8 illustrate the time and temperature profiles of experiments 4 and 5 that compose clusters 3 and 1, respectively. In experiment 4, factor levels were adjusted at -1 and 1. In experiment 5 levels were adjusted at 1 and 1.

Analyzing experiment 4, illustrated in Fig. 8, the reclosing time of the measured t_{P3} compressor in the test was 510 minutes and the t_{P3} time predicted by the successive approximation algorithm was 508 minutes, a difference of 2 minutes, meaning an error of 0.4% over the total time period of 8 hours and 30 minutes. In experiment 5, the reclosing time of the t_{P3} compressor measured in the test was 533 minutes and the t_{P3} time predicted by the successive approximation algorithm was 502 minutes, with a difference of 31 minutes, which means an error of 5.8 % over a total time of 8 hours and 53 minutes.

The final result of the experiments used to validate the prediction method presented an average absolute error of 2.7%. The calculated standard deviation was 2.8%, indicating that there was a greater dispersion in the t_{P3} prediction in experiments 5 and 6, influenced by the change in factor a - beverage volume, which increased from 32 liters in experiments 3 and 4 to 64 liters in tests 5 and 6.

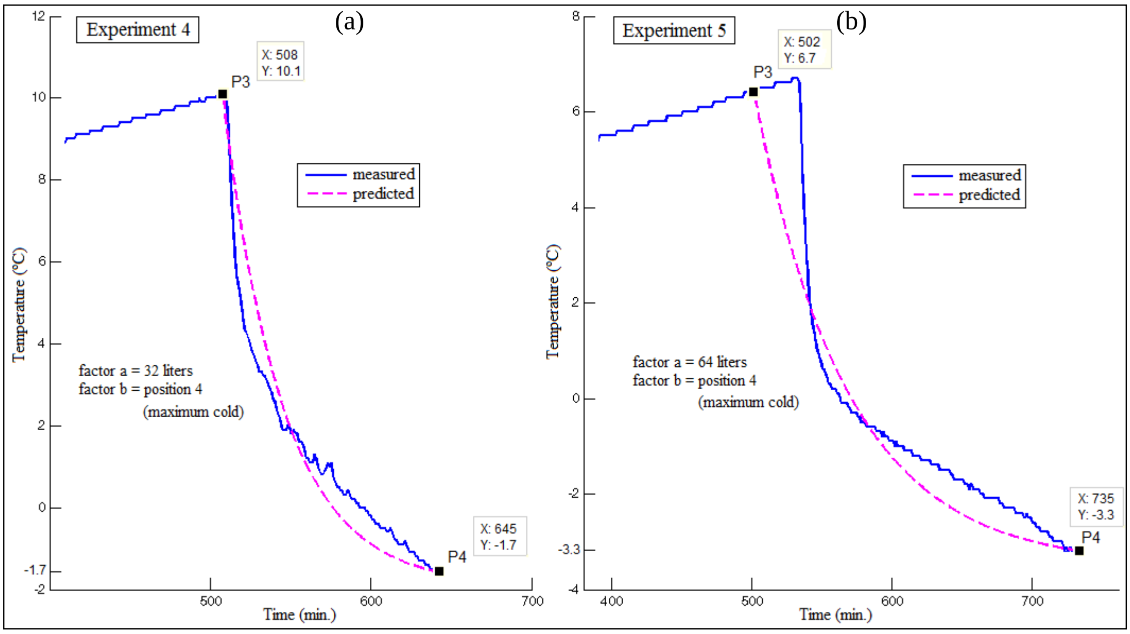


Figure 8. P3 time prediction: a) experiment 4 of group 3, b) experiment 5 of group 1.

4.3 Evaluation of electrical consumption of the refrigerator

An experimental investigation was performed to evaluate the electric energy consumption of the refrigerator, comparing two scenarios, the first with the equipment operating in continuous mode, performing normal refrigeration cycles (factor **c** in -1), and the second working in discontinuous mode with programmed time for shutdown outside of work shift (factor **c** in 1).

The experiments followed the randomized sequence determined by a factorial design matrix, totaling 16 samples with 8 runs, combining 2 levels of the 3 three factors, **a** - beverage volume, **b** - thermostat adjustment position and **c** - time off during work shift. The results obtained after performing the experimental investigation are shown in Table 3, together with the measured values of the daily electricity consumption by the refrigerator in Wh.

Table 3. Experimental results of energy consumption

Sample	**Run**	**Factor levels**			***E* (Wh) measured**
		a	b	c	
1	4	1	1	-1	2611
2	1	-1	-1	-1	922
3	5	-1	-1	1	716
4	7	-1	1	1	1360
5	8	1	1	1	2543
6	6	1	-1	1	958
7	2	1	-1	-1	1121
8	6	1	-1	1	817
9	4	1	1	-1	2785
10	2	1	-1	-1	1277
11	5	-1	-1	1	749
12	3	-1	1	-1	1779
13	7	-1	1	1	1537
14	8	1	1	1	2549
15	1	-1	-1	-1	962
16	3	-1	1	-1	1861

Table 4 presents the comparative result of daily energy consumption of the refrigerator, under the same combinations between factors **a** and **b**. In all test conditions it is found that the energy consumption is always lower with the proposed off-shift shutdown method compared to the operating mode without shutdown.

Evaluating the comparative energy savings of Tab. 4, applying the proposed method, it is noticed that the largest savings are obtained when the refrigerator is set to operate in the thermostat temperature adjustment position at level -1 (moderate cold). The result is even better if the cooler is filled with 64 liters of beverages, providing a saving of 26%. When the refrigerator is operating with a full beverage load (64 liters) and in the maximum cold position, the least economical condition is found, still achieving 5.6% of energy economy by applying the proposed method.

Table 4. Comparison of energy consumption between methods and economy by the proposed method

Factor levels		Daily consumption (Wh)		Daily saving by the proposed method (factor c= 1)	
a	b	without the proposed method (factor c= -1)	with the proposed method (factor c= 1)	Energy (Wh)	Energy (%)
-1	-1	942	733	210	22.2%
1	-1	1199	888	312	26.0%
-1	1	1820	1449	372	20.4%
1	1	2698	2546	152	5.6%

5. CONCLUSIONS

This work proposes a method for identifying the dynamics of a beverage cooling system and predicting the temperature stabilization time. The method described in this work results in the dynamic identification of parameters the Newton's Law of Cooling equation. This allows you to predict the cooling time of a beverage cooling system and generate electric energy savings without affecting the performance of its function. The theoretical model presented did not require any prior knowledge of the system's physical variables. Another contribution of the work was the ability of the method to dynamically update the system model when it was subjected to thermal load variation and / or change of temperature adjustment position on the thermostat. The results demonstrate a maximum error of 2.7% in predicting the compressor start time after the shutdown period. The energy savings obtained ranged from 5.6% to 26%, depending on the test conditions.

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