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Grey-box Modeling for System Identification of Household Refrigerators: a Step Toward Smart Appliances

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Abstract—This paper presents the grey-box modeling of a vapor-compression refrigeration system for residential applications based on maximum likelihood estimation of parameters in stochastic differential equations. Models obtained are useful in the view of controlling refrigerators as flexible consumption units, which operation can be shifted within temperature and operational constraints. Even if the refrigerators are not intended to be used as smart loads, validated models are useful in predicting units consumption. This information can increase the optimality of the management of other flexible units, such as heat pumps for space heating, in order to smooth the load factor during peak hours, enhance reliability and efficiency in power networks and reduce operational costs.

Keywords—Refrigerators, Stochastic processes, System identification, Load shifting.

I. INTRODUCTION

The World Business Council for Sustainable Development estimates that in most countries buildings account approximately for the 30-40% of total energy consumption [1]. Energy consumption in a building can be related to such applications as space heating and building automation (including security systems and ICT infrastructures) or to human activities. It emerges that controlling loads with building automation systems can enhance the overall demand flexibility and enable a win-win situation, where customers adjust their consumption upon economic inducements and utilities avoid grid overloads by spreading the demand during off-peak periods [2]. In this context, validated models of appliances are necessary in the design of systems for residential demand side management and in testing and benchmarking controllers for energy consumption in Smart Buildings.

Devices or processes associated to thermal storage present intrinsic flexibility in consumption as long as their operation is managed within certain comfort bounds. One example is space heating, which can be used for peak shaving [3], but also other types of thermal storages (such as refrigerators or water chillers) offer flexibility in consumption.

This paper presents the grey-box modeling of a vapor-compression refrigeration system for residential applications using stochastic differential equations (SDEs). The grey-box approach offers the possibility of providing a combined physical and statistical description of the system. The identified models are useful in the view of controlling refrigerators as flexible consumption units, which operation can be shifted within temperature and operational constraints. Even if the refrigerators are not intended to be used as smart loads, validated models are useful in predicting units consumption. This information can increase the optimality of the management of other flexible units, such as heat pumps for space heating, in order to smooth the load factor during peak hours, enhance reliability and efficiency in power networks and reduce operational costs. Household refrigerator modeling and performance assessment has been previously addressed with such approaches as dynamic simulation [4], steady state simulation [5], or CFD models [6].

The motivation to this study is to provide simple, ready-to-use and validated lumped parameter (stochastic state space) models for household refrigerators. The approach used is formed by forward model selection and validation based on experimental data and statistical testing. The software used is CTSM [7], which is based on maximum likelihood estimation. Parameters as thermal masses, evaporator thermal resistance, U-value of insulation and refrigeration cycle Coefficient of Performance (COP) are identified for each model in terms of expected value and variance. Convergence of estimation is also troubleshooting.

II. EXPERIMENTAL SETUP

The experimental setup consists of: household refrigerator of capacity 60 liters with freezer bay and single compressor, power meter DEIF-MIC2, ADAM-6024 ADC card, four calibrated temperature sensors TI-LM35, one remotely controlled power outlet. Every second the refrigerator internal temperatures, ambient temperatures and refrigerator active power consumption are synchronously measured. Given the stratification of temperatures in the refrigeration chamber, two sensors are used in order to provide the average internal temperature. The same approach is used for determining the ambient temperature.

The refrigerator thermostat is set to supply the minimum temperature such that it is possible, within a temperature range, to enable or disable the compressor operation directly via the controlled power outlet.

III. MODEL OF REFRIGERATION CYCLE

This section presents a simple model for vapor-compression refrigeration system based on steady state one-
dimensional heat transfer equations. It is deemed valid to develop a static model of the vapor-compression cycle since it has faster dynamics if compared to the cold storage. Figure 1 shows a schematic representation of common refrigeration system for household applications.

![Single stage vapor-compression refrigeration system.](image)

Fig. 1. Single stage vapor-compression refrigeration system.

A simple model of the system is:

\[
\frac{dQ_{cs}(t)}{dt} = \dot{Q}_{load}(t) - \dot{Q}_c(t),
\]

where:

\[
\begin{align*}
\dot{Q}_{cs} &= m_{cs}c_{cs}dT_{cs} \\
\dot{Q}_{load} &= UA_{cs}(T_a - T_{cs}) \\
\dot{Q}_c &= \dot{m}_r [h_o(p_e) - h_c(p_c)] \approx COP \cdot \Phi_c \\
\dot{m}_r &= N_e \rho \phi_r(p_e)
\end{align*}
\]

In Eq. 2, \(m_{cs}\) is the cold storage mass and \(c_{cs}\) is its specific heat capacity. \(h_o\) and \(h_c\) are the evaporation and condensation enthalpies at the evaporation and condensation pressures, respectively \(p_e\) and \(p_c\). \(UA_{cs}\) is the overall transmittance coefficient from the refrigeration chamber to the ambient and \(\dot{m}_r\) is the refrigerant mass flow rate. \(COP\) is the overall coefficient of performance, here defined as the ratio between \(\dot{Q}_c\), the thermal power extracted at evaporator side, and \(\Phi_c\), the refrigerator electrical consumption.

IV. GREY BOX MODELING

Grey-box modeling is a framework for identifying a system description that combines prior physical knowledge of the system with information obtained from experimental data. For parameters estimation and system control it is convenient to use stochastic state space models [8], where the dynamical part of the model, the state, is described by Stochastic Differential Equations (SDEs) and the output is given by a discrete time algebraic equation describing how the observations are linked to the state. The parameters estimation and uncertainty assessment is obtained with statistical methods [9]. A stochastic differential equation (SDE) is a differential equation where one or more terms are stochastic processes, so that the solution is a stochastic process itself.

This section presents three different models of increasing complexity, all of which are developed under the hypotheses of: homogeneous materials, linear cooling cycle with constant COP and neglect of freezer compartment.

It is convenient to use electric thermal equivalent models in order to easily depict the models’ structure and relate the identified parameters to physical quantities such as thermal transmittances and efficiency coefficients.

A. Model \(T_i\)

Here the refrigeration chamber is represented with a thermal mass, \(C_i\), while the envelope (insulation) is modeled with a pure thermal resistance, \(R_{ei}\) (Fig. 2):

\[
C_i \quad T_i \quad \text{Compressor} \quad R_{ei} \quad \text{Exp. Valve} \quad T_{evap} \quad R_{ea} \quad T_a
\]

Fig. 2. Refrigerator preliminary model (electric equivalent): \(T_i\).

The compressor has a direct refrigeration effect, so that it is modeled as a current generator. This model is a single state stochastic state space model:

\[
\begin{align*}
\dot{T}_i &= \left[ \frac{1}{c_i R_{ei}} (T_a - T_i) - \frac{1}{c_i} A_c \Phi_c \right] dt + \sigma_1 dw_1 \\
y_{t_i} &= T_{i,t_k} + \epsilon_{t_k}, \quad \epsilon_{t_k} \sim N(0, \sigma_{\epsilon}^2)
\end{align*}
\]

where \(A_c\) is the cycle COP and \(w\) is a standard Wiener process independent from the residual \(\epsilon_{t_k}\). \(T_a\) is the ambient temperature, \(T_i\) is the refrigeration chamber temperature and \(\Phi_c\) is the compressor active power consumption. Parameters’ units are:

\[
T_i = [^\circ C], \quad R_i = \left[\frac{\Omega}{m^2}\right], \quad C = \left[\frac{J}{^\circ C}\right], \quad A_c = [\text{scalar}], \quad \Phi_c = \left[\frac{kW}{^\circ C}\right].
\]

B. Model \(T_i T_{evap}\)

This model extends the previous one by accounting for the heat transfer between the refrigeration chamber and the evaporator. This leads to an additional state for the evaporator temperature, \(T_e\):

\[
\begin{align*}
\dot{T}_i &= \left[ \frac{1}{c_i R_{ei}} (T_a - T_i) + \frac{1}{C_{evap}} (T_e - T_i) \right] dt + \sigma_1 dw_1 \\
\dot{T}_e &= \left[ \frac{1}{C_{evap}} (T_e - T_i) - \frac{1}{c_e R_{evi}} A_c \Phi_c \right] dt + \sigma_2 dw_2 \\
y_{t_k} &= T_{i,t_k} + \epsilon_{t_k}, \quad \epsilon_{t_k} \sim N(0, \sigma_{\epsilon}^2)
\end{align*}
\]

where \(w_1, w_2\) and \(\epsilon_{t_k}\) are independent.

C. Model \(T_i T_{evap} T_e\)

Here the \(T_i T_{evap}\) model is extended by adding a state to the envelope and separating the envelope thermal resistance in inner resistance, \(R_{ei}\), and outer resistance, \(R_{ea}\):

\[
\begin{align*}
\dot{T}_{evap} &= \left[ \frac{1}{C_{evap} R_{evi}} (T_i - T_{evap}) - \frac{1}{C_{evap}} A_c \Phi_c \right] dt + \sigma_3 dw_3 \\
\dot{T}_i &= \left[ \frac{1}{c_i R_{ei}} (T_a - T_i) + \frac{1}{C_{evap}} (T_e - T_i) \right] dt + \sigma_2 dw_2 \\
\dot{T}_e &= \left[ \frac{1}{c_e R_{evi}} (T_e - T_i) + \frac{1}{C_{evap}} (T_a - T_e) \right] dt + \sigma_3 dw_3 \\
y_{t_k} &= T_{i,t_k} + \epsilon_{t_k}, \quad \epsilon_{t_k} \sim N(0, \sigma_{\epsilon}^2)
\end{align*}
\]
where \( w_1, w_2, w_3 \) and \( c_{tk} \) are independent. Follows the electric equivalent model:

\[
\begin{align*}
T & = T_{evap} = T_c.
\end{align*}
\]

Fig. 4. Refrigerator model (electrical equivalent): \( T, T_{evap}, T_c \).

V. A-PRIORI PARAMETERS

Grey-box modeling can benefit from calculated or judged value of parameters to be used as initial value for the estimation process. This section presents an initial estimation of physical parameters for the refrigerator chamber, including the glass shelves and the plastic drawer. The refrigerator insulation is assumed to be made by extruded expanded polystyrene (XPS).

A. Refrigeration chamber (thermal mass)

a) Air (0°C, sea level, dry air):

\[
\begin{align*}
&c_{v-air} = 1297 \frac{J}{m^3 \cdot K}, \\
&V_{air} = 0.111456 m^3 \\
&C_{air} = c_{v-air}V_{air} \simeq 145 \frac{J}{K}.
\end{align*}
\]

(6)

b) Glass (tempered glass):

\[
\begin{align*}
&V_{shelf(1,2)} = 8.25 \cdot 10^{-4} m^3, \\
&V_{shelf(3)} = 4.41 \cdot 10^{-4} m^3 \\
&\rho_{glass} = 2500 \frac{kg}{m^3}, \\
&m_{glass} = \rho_{glass}(2 \cdot V_{shelf(1,2)} + V_{shelf(3)}) = 5.232 kg \\
&C_{glass} = \rho_{glass}m_{glass} \simeq 4395 \frac{J}{K}.
\end{align*}
\]

(7)

c) Plastic (a rough estimation for the drawer):

\[
\begin{align*}
&\rho_{polyethylene} = 910 \frac{kg}{m^3}, \\
&V_{drawer} \simeq 7.996 \cdot 10^{-4} m^3 \\
&m_{drawer} = \rho_{polyethylene}V_{drawer} \simeq 0.65 kg \\
&C_{m-polyethylene} = 1.67 \frac{J}{g \cdot K} \\
&C_{plastic} = m_{drawer}\rho_{polyethylene} \simeq 1086 \frac{J}{K}.
\end{align*}
\]

(8)

d) Total thermal mass of refrigeration chamber:

\[
C_t = C_{air} + C_{glass} + C_{plastic} = 5626 \frac{J}{K}
\]

(9)

B. Envelope: thermal mass and resistance

It is reasonable to assume that the insulation layer has size: 44cm depth (D), 55cm height (H), 48cm width (L), and 3.5cm thickness (d):

\[
\begin{align*}
&\rho_{poly} = 50 \frac{kg}{m^3}, \\
&\rho_{m-poly} = 1.3 \frac{kg}{g \cdot K}, \\
&\lambda_{poly} = 0.033 \frac{W}{m \cdot K} \\
&S_{envelope} = 1.4344m^2, \\
&V_{envelope} = S_{envelope}d \simeq 0.043 m^3 \\
&m_{envelope} = \rho_{poly}V_{envelope} = 2.15 kg
\end{align*}
\]

\[
\begin{align*}
e) \text{Total thermal mass and resistance of the envelope:} \\
&C_e = m_{envelope}\rho_{m-poly} \approx 2797 \frac{J}{K} \\
&\lambda_{poly} \approx 0.74 \frac{K}{W}
\end{align*}
\]

(10)

C. Refrigeration cycle (COP)

Figure 5 shows the total thermal power acting on the refrigeration chamber versus the temperature drop. When the compressor is not operating, the thermal power coming from the ambient accounts for approximately 8W, whereas during the refrigeration cycle the total thermal power at the refrigeration chamber is approximately -30W. Therefore the compressor generates approximately -38 thermal watts with an average electrical consumption of 50 watts, so that an initial value of the COP is:

\[
COP \simeq 0.76.
\]

Fig. 5. Refrigerator operation: thermal power at refrigeration chamber v.s. temperature drop.

The COP could seem low, but notice that here it is approximated by the ratio between thermal power extracted from the refrigeration chamber and the electrical power consumed by the compressor and hence it includes also the mechanical and electrical efficiency.

VI. SYSTEM IDENTIFICATION

Parameter estimation is carried out using CTSN, which provides a tool for semi-physical modeling and identification of dynamic systems based on stochastic differential equations [10]. CTSN provides methods for estimating unknown parameters of the model from data, including parameters in the diffusion term, using either the maximum likelihood (ML) method [11] or the maximum a posteriori (MAP) method. Both methods allow for several independent data sets to be used and are both sound statistically based estimation methods, which means that once the parameters have been estimated, statistical methods can be applied to investigate the quality of the model [12].

Figure 6 shows the process of model identification and validation. A first set of data, called identification data (see Fig. 7), is used for estimating model parameters and initial values of the states. Then the model, using the power input and room temperature from the same identification data, is used to calculate the one-step ahead predictions of the output. These predictions are subtracted from the measured output to form the residuals, which are analyzed for their white noise properties. If the model prediction residual is statistically close to white noise, the model is good [9]; therefore the auto correlation function is used to analyze the residuals (see, eg., Fig. 9). This procedure is called model validation.

A model can also be validated with another data set (see, eg., Fig. 14). If the results are good, this procedure gives a good indication of model robustness and correct identification.
Figure 10 presents the residuals (top chart), the power input (mid chart) and the predicted and measured temperature in the refrigerator. From these plots it is possible to depict that model residuals are higher at the beginning of refrigeration cycle. Such situation was expected, since the non-linearities and complexity of the refrigeration cycle are not considered in the model. When the compressor is off, the prediction error is low and residuals are similar to white noise. Due to its inaccuracies and the identified missing dynamics from Fig. 9, this model is not further validated. In the next subsections, the second group of charts (e.g., Fig. 10) is omitted for brevity.

B. Parameters of the $T_iT_{evap}$ model

Table II. Identified Parameters: $T_iT_{evap}$ model.

<table>
<thead>
<tr>
<th>PARAMETER</th>
<th>VALUE</th>
<th>STD. DEV.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_{in}$</td>
<td>9.01e-8 · 10$^{-3}$</td>
<td>3.546 · 10$^{-2}$</td>
</tr>
<tr>
<td>$R_{evap}$</td>
<td>9.0348 · 10$^{-3}$</td>
<td>2.5121 · 10$^{-2}$</td>
</tr>
<tr>
<td>$C_i$</td>
<td>1.6600 · 10$^{-3}$</td>
<td>1.6529 · 10$^{-4}$</td>
</tr>
<tr>
<td>$C_c$</td>
<td>3.4342 · 10$^{-4}$</td>
<td>9.9157 · 10$^{-6}$</td>
</tr>
<tr>
<td>$T_i(0)$</td>
<td>14.774</td>
<td>1.9835 · 10$^{-2}$</td>
</tr>
<tr>
<td>$T_{evap}(0)$</td>
<td>16.181</td>
<td>3.6991</td>
</tr>
<tr>
<td>$A_e$</td>
<td>0.8383</td>
<td>2.6217 · 10$^{-2}$</td>
</tr>
<tr>
<td>$exp(\sigma_1)$</td>
<td>-1.7406 · 10$^{-1}$</td>
<td>5.6451 · 10$^{-2}$</td>
</tr>
<tr>
<td>$exp(\sigma_2)$</td>
<td>-8.9551 · 10$^{-1}$</td>
<td>2.6646 · 10$^{-2}$</td>
</tr>
<tr>
<td>$exp(\tau)$</td>
<td>-1.2246 · 10$^{-1}$</td>
<td>1.1364 · 10$^{-1}$</td>
</tr>
<tr>
<td>Loglikelihood</td>
<td>12096.4351</td>
<td></td>
</tr>
</tbody>
</table>

The residual analysis in Fig. 11 shows a clear improvement of model $T_iT_{evap}$ compared to $T_i$ and the cumulative periodogram is almost inside the confidence bands.

C. Parameters of $T_iT_{evap}T_e$ model

Model $T_iT_{evap}T_e$ outperforms in data fitting and the cumulative periodogram stays in the confidence bands. Figures 13
has the best performance. Therefore the choice of model $T_i T_{evap}$ as reference model for the given setup.

VII. Conclusion

This study showed an application of grey-box stochastic modeling for household refrigeration systems. Identified models are simple, reliable and, since they are SDE-based, they can be used for forecasting, control and simulation. Thanks to the diffusion terms, model uncertainties are also provided. This study represents for the authors a starting point for the development of intelligent control of such systems as thermal storages for providing power balancing services to the utility in a Smart Grid context.

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References


