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SIMULATION OF PRODUCT PERFORMANCE BASED ON REAL PRODUCT-USAGE INFORMATION: FIRST RESULTS OF PRACTICAL APPLICATION TO DOMESTIC REFRIGERATORS

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ABSTRACT

Today's connected products increasingly allow us to collect and analyze information on how they are actually used. An engineering activity where usage data can prove particularly useful, and be converted to actionable engineering knowledge, is simulation: user behavior is often hard to model, and collected data representing real user interactions as simulation input can increase realism of simulations. This is especially useful for (i) investigating use-related phenomena that influence the product's performance and (ii) evaluating design variations on how they succeed in coping with real users and their behaviors. In this paper we explored time-stamped usage data from connected refrigerators, investigating the influence of door openings on energy consumption and evaluating control-related design variations envisaged to mitigate negative effects of door openings. We used a fast-executing simulation setup that allowed us to simulate much faster than real time and investigate usage over a longer time. According to our first outcomes, door openings do not affect energy consumption as much as some literature suggests. Through what-if studies we could evaluate three design variations and nevertheless point out that particular solution elements resulted in better ways of dealing with door openings in terms of energy consumption.

1. INTRODUCTION

Product usage information (PUI) can be considered a valuable source of knowledge for predicting usage and behaviors of current and future products, and related services¹. With 'usage' we mean, in this particular context, the way users use the product and how they interact with it. It is not to be confused with 'usage' as consumption of resources and supplies, which we consider here as an aspect of product performance.

Traditional ways of collecting PUI include observation of human subjects and conducting user surveys. However, now that products are increasingly becoming equipped with their own capabilities of collecting use-related data, and a growing number of products is getting connected to the Internet, it becomes easier for manufacturers to collect data from fielded products [1].

In the EU-funded FALCON project (see Section 3), we have investigated the opportunities of exploiting such collected data in several ways. The main deliverable of this project was a software platform to collect and process data generated by connected products and related social media, with the objective to extract actionable knowledge that could be used as input for (re)design of products and related services [2]. One of the studies conducted in this context aimed to report on, and implement, methods and tools for forecasting and simulation based on *time-stamped* PUI, or TPUI – i.e., each data sample holds information about the time of usage or non-usage. Both forecasting and simulation enable predictions, i.e. descriptions of expected future processes as potential carriers of actionable knowledge.

On the one hand, TPUI potentially holds patterns that may repeat themselves in the future or represent trends that can be projected into the future. Applying methods and tools to that end is generally known as *forecasting*. It is typically based on data analytics and data mining, with data mining typically associated with computationally executed knowledge-discovery [3], and data analytics the umbrella term that also includes human tasks such as interpreting data visualizations [4].

Simulations, on the other hand, can be used to predict product performance under different circumstances, or of design alternatives. Having realistic usage data available makes it possible to (i) investigate the influences of different ways of using the product, and based on these, explore design variations tailored to

¹ Services are not addressed in this paper

these uses, and (ii) compare design variations under the same real-life usage circumstances.

The investigation of simulation potential in FALCON is the topic of this paper, which is structured as follows. In Section 2, we report on related work on simulations with data. Section 3 clarifies the role of simulations in the project. Section 4 introduces the simulation reference scenario provided by consortium partner Arçelik regarding the influence of usage and design considerations on energy consumption of a domestic refrigerator. Subsequently, Section 5 summarizes the relevant literature reporting on energy consumption of refrigerators, and how it is influenced by usage. Next, in Section 6 we discuss considerations regarding data collection and sampling. Section 7 presents our simulation model. Selection and preprocessing of the usage data is discussed in Section 8. In Section 9 we describe the simulation setup and the explored scenarios and Section 10 presents our first simulation results. In Section 11 we discuss these results, and, finally, in Section 12, we discuss what could be done next.

2. SIMULATION WITH DATA: RELATED WORK

Simulations are typically applied in the beginning-of-life stage of a product to evaluate design proposals based on mathematically defined behavioral models. Shannon [5] defined simulation as conducting experiments with an input-output model of a real system in order to predict probable future output of a system for a given input, to understand the system behavior and/or to evaluate system operation strategies. He points out that that gathering reliable input data can be time consuming and that questionable input data cannot be compensated by a good simulation model.

In many cases, products operate based on frequently applied and well-understood physics principles (e.g., electric motor, heat pump), that can adequately be captured in well-validated engineering simulation models. Yet, other processes may be involved that cannot be straightforwardly described by mathematical models, e.g., human behavior or the weather. This is where the dependability of the input data becomes crucial – consider for instance makeshift models that are created to generate input signals based on assumptions, such as pulse signals representing load patterns [e.g., 6,7]. Instead of such workarounds, we propose to use real-life TPUI, as it is increasingly becoming available from connected products.

A concept related to TPUI-based simulation is *data-driven simulation*, where data from the process to be simulated, corresponding to outputs as well as inputs of the simulation model, is used to optimize the simulation model [e.g., 8]. In some cases, data from an ongoing process is even used to continuously fine-tune a simulation that is running ahead [e.g., 9].

In the case of TPUI-based simulation, real-life data is only used as simulation *input*, while the simulation model itself is considered to be sufficiently dependable. Hence, it is assumed that the simulation results, can be used to (i) evaluate the performance of the product in realistic circumstances, (ii) identify mismatches between assumed inputs and real inputs, (iii) support finding directions to improve the design based on (i) and/or (ii), and (iv) evaluate (virtual simulation models of) alternative designs based on real inputs.

Our focus has been on input data that represents human (inter)actions. To add realism to simulations if inputs by human users have to be considered, interactive simulations with real humans in the loop [e.g., 10,11] have been put forward. These have the drawback that they must run in real time and cannot be accelerated to investigate usage over a longer time interval [12]. Moreover, deploying real users in testing is known to be expensive [13]. Figure 1 illustrates how TPUI from real-life usage of fielded products can fill the gap by providing realistic human inputs and thus contribute to more realistic results [14], without the need to slow down to real-time execution or recruit human subjects.

Our literature search revealed that in most other reports on product simulations with TPUI, also output data was processed in a data-driven simulation setup, and the focus was on optimizing models – particularly discrete-event simulation models of manufacturing systems [15–17]. A notable exception is the work reported by Pei et al. [18], who did not only compare and optimize different simulation models of electronics-packaging degradation based on TPUI from 100 mobile computing devices, but also used the simulation results to derive more realistic requirements for next-generation designs. However, their research was a one-time trial, with TPUI-collection capabilities added to product units just for this particular study. In such a case, researchers can optimally match the collected amounts and frequencies of data to their needs. TPUI-recording products often impose practical limits restricting the amount of available simulation input data.

A rare example where PUI was only used as simulation input, and not for optimizing simulation models, was reported by Urban and Roth [19]. In simulations comparing performance of smart thermostats, temperature set-points based on real values collected from end users were used. However, these simulations used fixed constellations of set-points per user, i.e., non-time-stamped, whereas our intention is to consider dynamically changing inputs to dynamic simulations.

3. SIMULATIONS IN FALCON

In the FALCON project we aimed to obtain actionable information from conventional engineering simulations through exploitation of TPUI. In that context, ‘actionable’ means

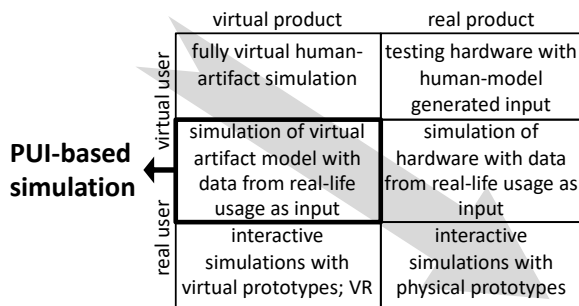


Figure 1. Filling the gap between virtual-user input and real-user real-time input (arrow depicts increasing realism)

providing insights in how the product can be improved in terms of performance, by a design that better anticipates actual usage. Here, ‘performance’ denotes any output measure that determines the quality of the product’s functioning to any involved stakeholder. Examples of performance indicators are speed of operation, supplies consumption, noise production, and quality of product outputs.

Our reasoning has been that dynamic simulation with TPUI as input can only produce actionable information with added value if the investigated performance measure of the product (i) can actually be assessed based on the simulation results and (ii) is influenced by the timing of changes in the TPUI.

As prerequisite (i) suggests, some performance measures *cannot* be assessed based on simulation results. This is for instance the case for subjective performance measures, such as the taste of coffee produced by a coffee maker.

Concerning (ii), for many products the available PUI is likely to represent the type, intensity and timing of user interactions. If, for instance, we consider a washing machine, the predominant interactions are program selection and inserting/removing the laundry. The *timing* of these interactions usually does not influence typical performance measures such as energy consumption and program duration. These are determined by what happens when the program is executed, *after* program selection and laundry insertion and *before* laundry removal – in other words, there is no direct interplay between user interactions and the part of product operation that determines performance, unless the user interrupts program execution – which can be considered an exceptional case. In order to assess performance, the simulation only needs the input parameters related to user interaction for each washing cycle (i.e., selected program and characteristics of the laundry), not their timing: the implicit assumption that these inputs have taken place before the start of the program is enough. Except for determining the total time span of data collection, the time stamps have no added value.

In the case of a refrigerator, on the other hand, there is direct interplay between interactions with its doors and its contents and the part of product operation that determines performance, which is actually its continuously ongoing. In this case we need to consider use interactions *with their timing* as input for dynamic simulations. The effect of two door openings of 5s at 10s apart is likely to differ from the same openings at 60s apart.

With the simulations, we aimed to perform what-if studies to assess the influence of interactions (door openings) on performance measures – energy consumption and temperature of stored food items – and to explore, by comparison, design variations that may potentially compensate for negative effects of the interactions.

The main deliverable of the FALCON project was a virtual open platform (VOP) that enables, among other things, the collection of TPUI and performing descriptive analytics on the collected data. The VOP supports simulations by offering a *Data Export Module* that converts user-specified selections from the collected data to a comma-separated values (CSV) file, a basic table format that can be read by most simulation packages. The user-specified selection of the TPUI to be listed in the CSV file

is handled by a VOP module called *PUI query builder*, which works together with another module responsible for Knowledge Consolidation & Cross sectoral Management (KCCM) [2].

4. REFERENCE SCENARIO: EFFECT OF DOOR OPENINGS ON REFRIGERATOR POWER CONSUMPTION

To demonstrate the potential of TPUI-based simulation a simulation model was implemented to explore a business scenario provided by Arçelik, a consumer electronics and household appliance manufacturer based in Turkey, partner in the FALCON consortium and envisaged user of the VOP. In this scenario, a product development team wants to exploit TPUI by performing what-if type simulations to explore improvement options for upcoming refrigerator models, or firmware updates for the current model. For simulation modeling and execution, we have used MATLAB/Simulink™, as it is widely used for engineering simulations [20], and provides a basic refrigeration model that we could adapt and extend for use in our investigations.

The concrete case that we elaborated concerned an investigation on how the door openings by the end user affect energy consumption, and/or the course of the inside temperature. To that end, the VOP user starts out using the PUI Query Builder and the KCCM to select a representative refrigerator unit – for instance a ‘worst-case’ sample of which the doors are opened very frequently. Using the Data Export Module in conjunction with the KCCM, they create a CSV file that can be read by Simulink. In the Simulink simulation, the effect of the selected users’ door-opening behavior on energy consumption can be studied. Based on these outcomes different control regimes for the thermostat and/or the interior fan can be considered and the influence on these regimes on the energy consumption can be evaluated.

5. ENERGY CONSUMPTION OF REFRIGERATORS: RELATED WORK

The influence of door openings on the performance of refrigerators is subject of ongoing debate [21]. The frequency and duration of door openings have influence on the thermodynamic performance and the energy consumption of a refrigerator [22]. On the one hand, there are authors who point out that other use-related factors, such as temperature setting and room temperature have a much stronger influence [23], on the other hand, with other factors constant, door openings are reported to increase energy consumption by 1-8% according to several sources reviewed in [24]. Considering that the refrigerator is known to be one of the largest electricity consumers in a household – for instance, according to data from [25], refrigerators, refrigerator-freezer combinations and freezers are accountable for 33.6% of the total electricity consumption per household in the United Kingdom – reducing the influence of door openings can have a large impact. However, note that in countries where HVACs are common, the relative share will likely be lower.

To investigate the influence of door openings, *simulations* have also been devised [26,27], but the door-opening patterns in these simulations were not based on data collected from real usage. Also, the papers reporting on these simulations do not

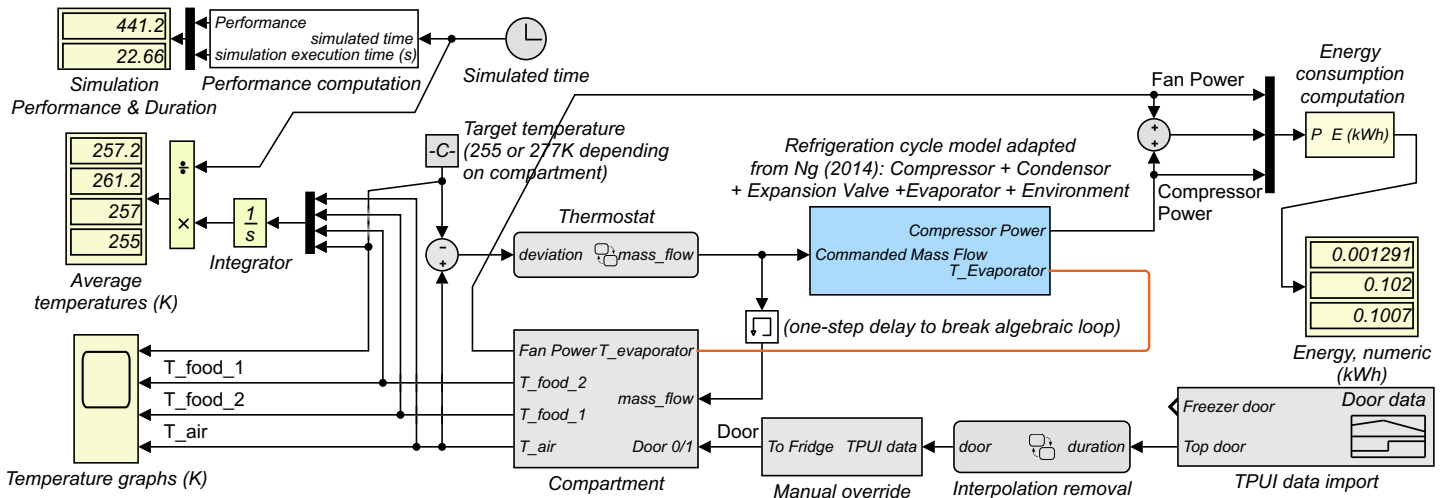


Figure 2. Refrigerator simulation model

discuss the simulation speed, and therefore we can assume that investigating longer periods of use, as in our case, has not been considered.

6. DATA COLLECTION AND SAMPLING CONSIDERATIONS

The original data produced by Arçelik’s connected refrigerators contains time-stamped values of readouts from various sensors. The defaulted interval between successive readouts is $t_{sample} \approx 1h$. Among these are (i) the end time of the interval (the time stamp), (ii) the total door opening times for the top and bottom – freezer – compartment, and (iii) the numbers of door openings during the elapsed interval. These and other readouts, such as compartment temperatures, can be selected for inclusion in the CSV file using the PUI Query Manager.

Currently, exact timings of door openings are not included: To further increase realism in simulations, data would have to be collected at shorter intervals. For now, we have approximated the occurrence of door openings by taking the total opening time per hour, starting at the time of data transfer. If during the interval $(t_{transfer} - t_{sample}, t_{transfer}]$ the door has been open n times for the cumulative duration

$$\Delta t_{open}(t_{transfer}) = \sum_{i=1}^n \Delta t_{open,i}$$

with the individual $\Delta t_{open,i}$ not specified in the data, we have simulated that, starting at $t_{transfer}$, the door was open for $\Delta t_{open}(t_{transfer})$. With this processing scheme, a future setup in which event-based data transfer provides data at the end of every door opening, so that $n = 1$ for each transfer and $\Delta t_{open}(t_{transfer})$ is no longer cumulative, would enable us to simulate the actual door openings.

7. SIMULATION MODEL

Figure 2 shows our simulation model of the refrigerator. It is based on a refrigeration model provided with Simulink [28]

(Refrigeration cycle model [...]), which was modeled using Simscape, a Simulink environment for simulating physical systems. As our main goal was to investigate the opportunities TPUI-based simulation offers for conducting what-if studies, we have not spent efforts in fine-tuning the simulation model so that it gives the best possible behavioral approximation of a particular specific refrigerator design. Assuming that door-opening behaviors in using refrigerator-freezer combinations do not depend on the particular make of the appliance, our investigations in this paper can be said to apply to a hypothetical refrigerator design and variations on it. This way, we also did not have to expose company-confidential design information.

To consider the effect of door openings we applied the following modifications and extensions (names in *italics* refer to block names in Figure 2):

1. Adding a *TPUI Data Import* block to import the CSV file using the ‘Signal Builder’.
2. Adding a Stateflow chart *Interpolation removal* to remove meaningless interpolated values that the Signal Builder adds between entries in the CSV file. Stateflow is a Simulink environment for modelling decision logic based on state machines and flowcharts.
3. Adding a subsystem *Manual Override* to allow interactive checking of the effect of door openings (Figure 3). It consists of two manual switches, which toggle between their two input ports if the simulation user double-clicks on them,

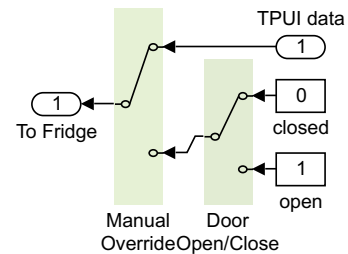


Figure 3. Manual override.

even while the simulation is running. To use the TPUI data, the left-hand switch is set as shown in Figure 3. In the other position, the simulation interactively receives its door openings from the bottom switch. To run a reference simulation with the door closed all the time, the manual input is permanently set to its ‘0’ port. A comparison of this reference situation with a simulation based on TPUI reveals the actual influence of door openings.

4. Modification of the Simscape model of the *Compartment* of the refrigerator. A starting point for this compartment model was provided in [28] as well, but it was considerably altered to include the effect of door openings in its heat management. Also, a compartment fan was added to ‘upgrade’ the model to that of a frost-free refrigerator with interior fan, in accordance with Arçelik’s connected refrigerators. The design variations that we wanted to compare are: (i) no fan, (ii) a fan that is controlled based on compressor activity only and (iii) a controlled fan that is off as long as the door is open. More details on model modifications are described after this listing.
5. Replacing the relay that was used to model the *Thermostat* by a Stateflow chart, to allow more complex control regimes for the compressor in what-if studies.
6. Adapting values regarding dimensions, etc., to values corresponding to those of a typical household refrigerator.
7. Creating outputs to allow assessment of (i) energy consumption by the compressor and the fan (*Energy, numeric*), and (ii) *Average temperatures* inside the compartment, including some food items. These are the performance measures targeted by our investigations. In addition, graphical output of the temperatures as a function of time is provided by the block *Temperature graphs*.
8. Adjusting the simulation duration to start and end times from the CSV file.

Figure 4 shows the adapted model of the refrigerator compartment to allow investigation of door openings. We added a subsystem *Door Influence [...]* that reacts on the door-opening data. We also added two blocks representing food items in the refrigerator, one of which has as its initial temperature the initial ‘cold’ starting temperature of the refrigerator interior, and the other is initially at room temperature, i.e., it represents food that has just been put into the refrigerator. The Evaporator Convection block is a var-convection block that is discussed in

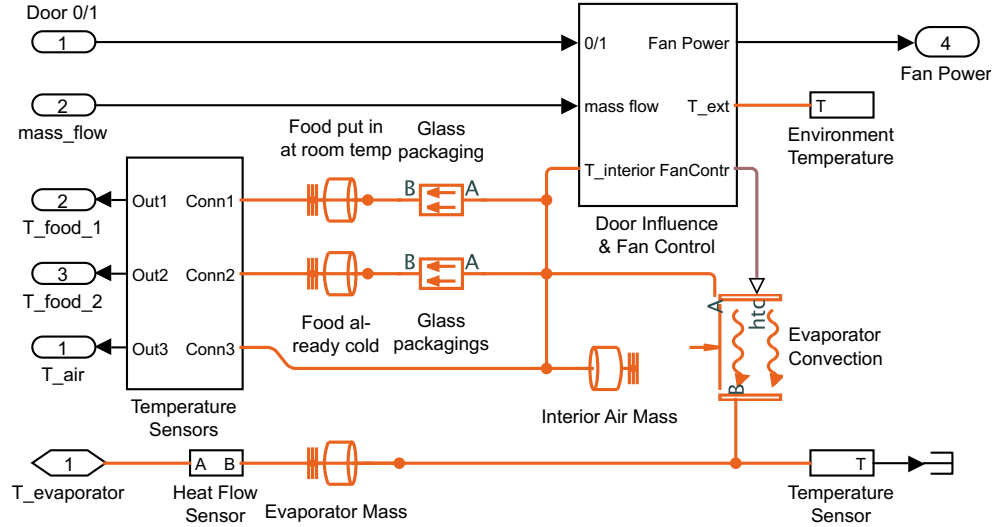


Figure 4. Simscape model of the compartment

the next paragraph. Its convection coefficient is an input signal, based on which it can represent the situation with no fan, with a non-controlled fan and with a controlled fan.

Figure 5 shows the ‘Door Influence & Fan control’ subsystem. It features custom blocks which are modifications of the standard blocks for heat convection and heat conduction between two points, i.e., in our case between the inside and the outside of the refrigerator. Instead of having a fixed value for the convection coefficient, the varconvection block ‘Door convection [...]’ takes a variable value as input from an input port. In our model, this variable is controlled by the Statechart shown on the left. Likewise, the varconduction block ‘Insulation [...]’ receives a variable for the insulator area, which is reduced by the size of the door if the door is open. The logic of the Statechart is shown as a truth table in Table 1.

The top compartment and the freezer compartment each have a 3W fan. Through iterative exploration we found that optimum positive influence on the energy consumption is achieved if the fans are synchronized with the compressor, with the switch-on timing delayed by 21s for the top compartment and 141s for the freezer, while switching off at the same time as the compressor for the top compartment and delayed by 18s for the freezer. These timings were implemented in the same Statechart.

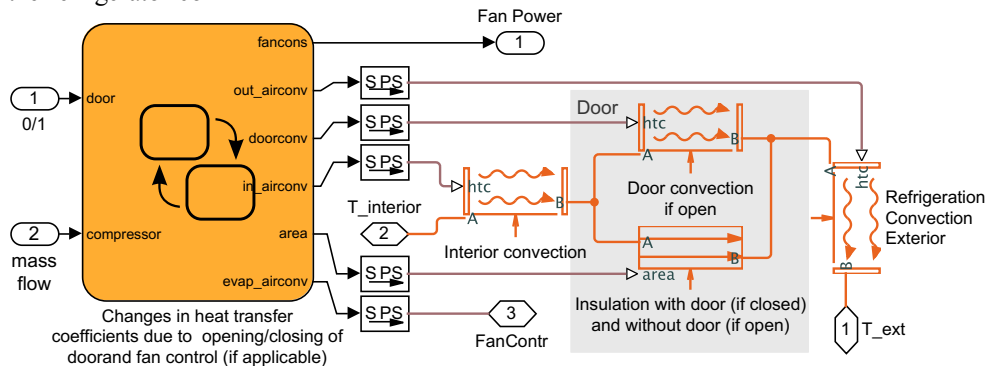


Figure 5. Simulation model of door influence and fan control

Table 1 Influence of door openings on heat transfer mode

Door	Fan	Heat transfer		Door	Outside
		Evaporator	Interior		
closed	off/absent	natural convection	natural convection	conduction	natural convection
closed	on	forced convection	forced convection	conduction	natural convection
open	off/absent	natural convection	natural convection	infinite conduction* and convection**	infinite convection**
open	on	forced convection	infinite convection**	infinite conduction* and convection**	infinite convection**

*enabled by reducing area in varconduction block to include only walls, bottom and top; ** based on the principle that if the door is open, there should be only one heat-transport barrier (convection or conduction) between the inside air and the outside (if the door is closed, there is convection on both sides of the door).

8. INPUT DATA: PRODUCT USAGE INFORMATION

The data that we used originated from 43 fielded refrigerator units collected over a 432-days’ time span. The total number of samples over all units was 67,234, out of which 7,826 turned out to be duplicates. Figure 6 shows some overall statistics, after removal of duplicates, obtained with RapidMiner™ data-mining software. The data-collection time span per unit varied from 0 to 431.7 days (Figure 6a). The majority of units collected data for less than 200 days. The seven units that collected data for less than one day were excluded from further analysis. Figure 6b shows the average number of data samples collected per unit per day for the remaining 36 units. Ideally, this number should be 24 (one sample per hour) but the majority of the units present a considerably lower sample density. The lower numbers of data samples in this figure can partially be accounted to units that were installed after the beginning of the data collection period, but further analysis also revealed time gaps in the data series: in total, the data contained 202 gaps of more than a day, each unit showing one or more such gaps in its data series. Since these gaps cannot be ascribed to lack of user interactions – which would have led to data samples reporting zero door openings – we have assumed that they are caused by connectivity problems.

To get a first impression of how the units installed in different households compare in terms of door-openings, we extracted the average time the freezer of each unit was open each day. We focused on the freezer compartment first, because it uses the bulk of the total energy. The distribution of the average daily freezer-open duration shown in Figure 6c. It suggests that, on average per day, the majority of users opens their freezer for only a few seconds, but that there are a small number of users that open their freezer for more than 20s. However, the averages in this result concern the whole dataset per unit, including possible multi-day gaps, from the first day until the last day they were online.

To obtain ‘cleaner’ data, intervals lacking long gaps had to be selected manually. We selected 9 out of the 36 units that covered a reasonable spread over the daily open durations in Figure 6c, and for each, selected the longest possible contiguous interval of samplings that did not contain gaps of more than a day. The overview of the selected refrigerators in Table 2 shows that the

average daily open duration over the whole observed interval is not proportional to the daily average over the simulated contiguous intervals.

Table 2 Overview of simulated refrigerator units

	unit	A	B	C	D	E	F	G	H	J
average daily	all-time	24.5	0.4	0.9	41.2	4.2	1.2	0.5	2.2	2.2
freezer open duration, s	simulated interval	14.6	27.5	1.9	41.2	5.3	1.9	2.0	4.0	4.0
	length of simulated interval, days	46.2	15.1	50.8	21.2	49.4	51.3	32.8	15.8	27.9

9. SIMULATION SETUP AND SCENARIOS

Figure 7 shows an example of typical simulation output. Since in simulations based on TPUI interesting phenomena in the graph are too far apart in time to produce an illustrative picture, it was created interactively by manually operating the switch in Figure 3. Figure 7 shows the course of the temperature in the compartment, as well as the temperatures of already-cold food (T_food_1) and the just inserted food at room temperature (T_food_2). The influence of door openings is obvious (annotated as ‘door open’ and ‘door closed’, respectively). The figure also gives evidence of a boot-up effect that reflects the commissioning of the refrigerator. Since this is a one-time event that is atypical for everyday steady-state use, we have eliminated its influence by ignoring the first 4,000 seconds of each simulation.

The actual refrigerator from which the data was collected uses one compressor for both compartments. We simplified this set-up by running separate simulations for the top compartment and the freezer unit, each with their own door-opening data and set temperatures (277K and 255K, respectively), and merged the results afterwards. Consequently, we also did not consider heat exchange between the two compartments.

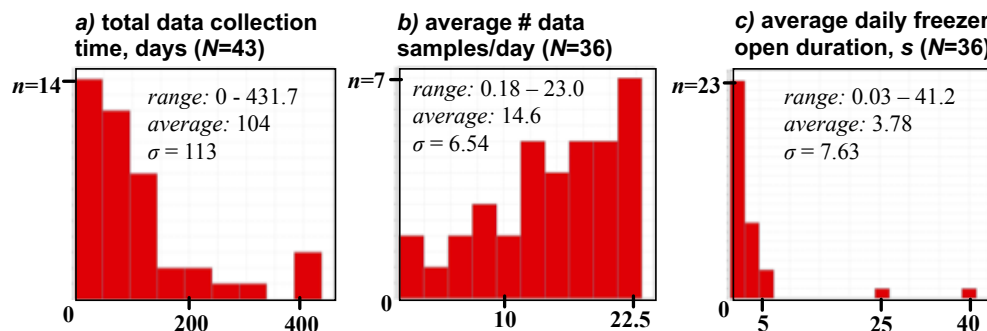


Figure 6. Statistics of collected refrigerator data

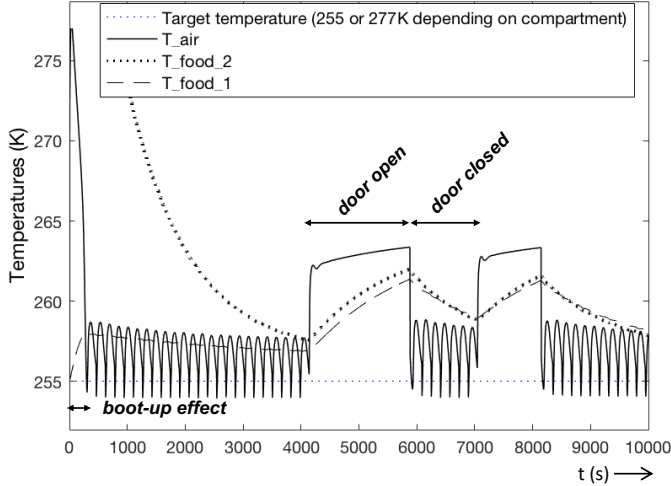


Figure 7. Simulation output with annotations

To complete our base scenario, we have assumed that the refrigerator was situated in a kitchen in Turkey with room temperature $296K$ ($73^{\circ}F / 23^{\circ}C$). The three design variations specified in Section 7 (number 4 in the listing), each applied to the two compartments, provided six what-if scenarios to be simulated, and to be combined to represent the refrigerator as a whole.

Apart from the performance of the refrigerator according to the simulation model, we also measured the performance of the simulation itself. According to [12], where it was applied to unrelated other simulations, simulation performance can be defined as

$$p_{sim} = \frac{T_{virtual}}{T_{sim}}$$

where $T_{virtual}$ is the time elapsed in the virtual, simulated world and T_{sim} the duration of the simulation computation on a given system. A value $p_{sim} > 1$ indicates a performance p_{sim} times faster than real-time.

10. OBTAINED RESULTS

10.1. Refrigerator performance and influence of door openings

In Table 3 we have brought together our simulation outcomes for the freezer compartment. The relative influence of door openings on the energy was calculated as a percentage, based on comparing a scenario with TPUI input with a reference

scenario in which the door was always closed, all other options being the same.

Beneath the double line, the table shows the outcomes of our three scenarios for the freezer. In the reference scenario with closed door the energy consumption is 0.80 kWh/day , which is reduced by 0.03 kWh/day with a fan (both variants). For three units we have also simulated the use of the top compartment. The results are shown in Table 4, together with the consequences for the refrigerator as a whole. In the reference scenario, the top compartment consumes 0.057 kWh/day , which is reduced by 0.002 kWh/day with a fan.

In all investigated cases, the relative influence (%) of door openings is larger for the top compartment than for the freezer, and, on the other hand, the absolute influence (kWh) is larger for the freezer. The largest relative influence, namely about 6% increase of energy consumption caused by door openings, could be seen in the case of a fan controlled by the compressor only, in the top compartment. This is an unlikely design choice (and therefore not included in Table 4), since practically every refrigerator has lighting in its top compartment, operated by a door-controlled switch that, at the same time, can easily be deployed as a door-open sensor to control the fan. For the freezer compartment this is different, since – unlike the Arçelik refrigerators from which we collected data – many refrigerators have no door sensor and lighting in the freezer compartment. Here, the design variant with fan that is controlled based on compressor activity only is a realistic design choice that is worth to be evaluated and that, of all remaining options, shows the largest absolute increase of energy consumption as a consequence of door openings.

Based on the computed daily consumption rates shown in the tables, the yearly energy consumption can be derived in order to validate the realism of the simulation model through comparison with findings from literature. In our case, the total energy consumption would be in the range of $330\text{-}340 \text{ kWh/year}$. Considering that the investigated refrigerator-freezer is a recent model, and that average energy consumption values from the literature typically include older units [22,24] while energy savings advance with every next generation of refrigerators [29], this appears to be consistent with the averages of 390 kWh/year that Biglia et al. [30] found from 483 fielded refrigerator-freezers, in which, on average, the freezer was set at $2.5K$ colder than in our simulation and the top compartment at $1K$ warmer.

Regarding the average temperatures that were computed in the simulations, it can be said in all cases that the temperature of the air in the compartments averaged at exactly the set value,

Table 3. Overview of simulation outcomes (freezer compartment)

	unit	A	B	C	D	E	F	G	H	J	average
average daily freezer open duration, s (simulated interval)		14.6	27.5	1.9	41.1	5.3	1.9	2.0	4.0	4.0	11.4
average daily freezer open frequency (simulated interval)		5.5	9.4	1.0	10.0	3.3	1.5	1.0	3.4	2.1	4.1
length of simulated interval, days		46.2	15.1	50.8	21.2	49.4	51.3	32.8	15.8	27.9	34.5
influence of door openings on energy consumption	no fan	0.14%	0.17%	0.02%	0.24%	0.03%	0.02%	0.08%	0.08%	0.22%	0.11%
	fan controlled by compressor only	1.15%	1.20%	0.33%	1.59%	0.47%	0.30%	0.57%	0.57%	0.37%	0.73%
	fully controlled fan	0.34%	0.34%	0.25%	0.37%	0.26%	0.23%	0.33%	0.33%	0.23%	0.30%

Maxima in **bold**, minima in **bold italics**

Table 4. Simulation outcomes including top compartment

unit	A		D		G		
average daily top compartment open duration, s	39.2		14.6		27.5		
average daily top comp. open frequency	10.0		5.5		3.4		
length of simulated interval, days	46.2		21.2		32.8		
	top comp.	both comp.	top comp.	both comp.	top comp.	both comp.	
influence of door openings on energy consumption	no fans	0.50%	0.16%	3.82%	0.48%	0.27%	0.05%
	freezer fan controlled by compressor only, top fan fully controlled	0.51%	1.11%	3.09%	1.69%	0.39%	0.32%
	fully controlled fans	0.35%		0.55%		0.25%	

Maxima in **bold**, minima in **bold italics**

while the temperatures of the included food items were always slightly lower in the top compartment and slightly higher in the freezer compartment. Influences of the various design choices and door openings were marginal and did not indicate the existence of a consistent relationship explaining the differences.

10.2. Simulation performance

To conduct the simulations, we relied on hardware with a level of processing power that is easily accessible within typical engineering environments². Overall, simulation performance was between 450 and 1050, with values around 1000 for the top compartment and around 550 for the freezer. We could not find any evidence indicating that having to import and process TPUI would slow down the simulations.

10.3. Regression analysis

To investigate whether our simulations could be replaced by a single generalized relation to predict the relative influence of door openings d based on daily opening duration t and frequency f , we applied regression analysis. As input we used the values from the scenario “fan controlled by compressor only” applied to the freezer compartment, i.e., the scenario with the largest absolute impact. To that end we used the Regression Learner app in MATLAB, which offers semi-automated analysis using 23 different regression models. The best fit resulted from a simple linear regression model $d = \alpha + \beta \cdot t + \gamma \cdot f$, with $\alpha = 3.05E-03$, $\beta = 2.08 \cdot 10^{-4}$ and $\gamma = 4.48 \cdot 10^{-4}$, found after 6-folds cross validation, with root mean square error $RMSE = 1.74 \cdot 10^{-3}$. This error is rather large considering that the response values are in the range 0 to 2% (0 to $2 \cdot 10^{-3}$). Table 5 demonstrates that the practical value of predictions based on the regression model is indeed limited.

We also explored whether a model could be found that provides an (almost) exact fit if no validation is applied. The existence of such a model might indicate that, after validation with more training data, the simulation can indeed be replaced by one relation that provides the simulation end results much faster. The best fit was provided by an exponential Gaussian process model with $RMSE = 6 \cdot 10^{-4}$, which we consider still too far from an exact fit to merit further investigation, especially since it is a more complex model and therefore more prone to overfitting [cf. 31].

Table 5. Predictions based on linear regression

unit	avg. daily		door-opening influence	pre-diction	prediction deviation			
	freezer open duration	avg. daily freezer open freq.			absolute error	absolute error	relative error	relative error
A	14.62	5.52	1.15%	0.86%	0.293%	0.293%	25.5%	25.5%
B	27.52	9.39	1.20%	1.30%	-0.099%	0.099%	-8.2%	8.2%
C	1.89	1.04	0.33%	0.39%	-0.061%	0.061%	-18.6%	18.6%
D	41.15	9.96	1.59%	1.61%	-0.018%	0.018%	-1.1%	1.1%
E	5.34	3.32	0.47%	0.57%	-0.095%	0.095%	-20.2%	20.2%
F	1.91	1.48	0.30%	0.41%	-0.112%	0.112%	-37.2%	37.2%
G	2.01	1.01	0.57%	0.39%	0.178%	0.178%	31.1%	31.1%
H	3.99	3.42	0.57%	0.54%	0.028%	0.028%	4.9%	4.9%
J	4.02	2.12	0.37%	0.48%	-0.114%	0.114%	-30.7%	30.7%
avg.	11.38	4.14	0.73%	0.73%	0.000%	0.11%	-6.1%	19.74%

11. DISCUSSION AND CONCLUSIONS

Using TPUI as input for dynamic simulation models only makes sense if performance measures are investigated that are actually influenced by the timing of changes in the TPUI and if these measures form an assessable part of the simulation outputs. A domestic refrigerator is a typical product that lends itself for such simulations: an important, quantitative performance measure is its energy consumption, which is dynamically influenced by detectable user interactions while the refrigerator is operating and consuming energy.

In this paper we presented first results of using simulations to assess the effect of user interactions (door openings) on performance (energy consumption) of a product (refrigerator), and to review, in various scenarios, how possible design variations can influence these effects. To allow using TPUI as input during simulations we created custom simulation-modeling elements that accept input signals in order to vary values that are normally assumed to be constant. Door openings and closings could effectively be modeled by varying areas and heat transmission properties of refrigerator construction components during runtime. Although our approach and the available hardware allowed us to perform simulations at a speed of 450-1050 times real-time and investigate use over a longer time interval, an average simulation run still took 1-2 hours, which, so far, limited us to investigating only three units with both refrigerator compartments and different control-regime variations as well as accompanying reference scenarios (with door always closed), and six additional units where this was done for the freezer only – which has the largest impact. Based on our findings, we could at least assess some of the statements regarding influence of door openings that we cited in Section 5. It turns out that even when the doors are being opened rather frequently, the lower end of the 1-8% range mentioned in [24] was reached, but only if the freezer compartment has a fan that does not react on door openings. In the corresponding design variation in our simulations, door openings had a 0.57 up to 1.66% impact on energy consumption. In such refrigerators it might be worthwhile to consider adding a door switch to control the fan, or not to have a fan in the freezer compartment. Obviously, the latter is not an option as the fans also have a role in defrosting, which we did not consider in our model. At any rate,

² 2017 Apple MacBook Pro with 3.1 GHz Intel Core i5 processor and 16 GB of RAM, which was also used for other tasks in parallel.

considering the fact that a refrigerator substantially contributes to a household's overall electricity consumption, even attempts to deal with the small influence of door openings that we found in our investigations could make sense.

What we did not include in our simulations was the putting in and taking out of food items that goes together with door openings. Items that are put in typically have a higher temperature than the compartment, which might partly explain the differences with findings from literature. With the sensing technologies currently implemented in refrigerators, it does not seem likely that such data can be added to the TPUI already collected. Another factor of influence could be the inclusion of older, less efficient refrigerators in the field studies discussed in [24].

The fact that we could not identify an equivalent regression model to replace the simulations seems to confirm that TPUI as input for simulations offers added value compared to synthetic data such as cyclic load patterns. Apparently, the more complex and/or irregular usage patterns captured in the TPUI lead to results that cannot be predicted based on average door-opening times and frequencies alone. However, if we would extract more features from the data, such as for instance average times between door openings, it might be possible to find a suitable equivalent model after all. In that case, only a limited series of simulations based on TPUI might be enough to derive a sufficiently reliable model based on regression or some other machine-learning approach. Once such a model would be available, fast predictions of the influence of use patterns based on a limited set of features extracted from the data would be conceivable. However, such models do not lend themselves to incorporation of design modifications, and can therefore not be used to evaluate design alternatives.

The possibility to exploit TPUI by performing simulations is likely to have impact on the way future products will be designed. Firstly, in designing each first generation of a product range to collect and transfer data, anticipative consideration must be paid as to what data collection capacities will be included in the design. For example, in the case of refrigerators, changes in ambient temperature are known to affect the performance. Since the investigated refrigerators were not equipped with external temperature sensors, we could not investigate this effect. Moreover, if the refrigerator would be able to keep track of its own energy consumption, simulations would no longer be useful in the case where only effects on the current design would be studied – but they would still add value if design alternatives are to be explored.

Secondly, once product units are out on the market, TPUI-based simulations can be used to study how real-life usage affects performance. If certain manifestations of usage emerging from the data raise suspicion of negatively affecting performance (as in our case the door openings), comparison with reference data that lack these manifestations (in our case fictitious input with the door always closed) can reveal the severity of the problem. If serious enough, designers can ideate possible solutions to mitigate the negative effects, implement these in the simulation model and run simulations with the real-life data to compare the effectiveness of the proposed solutions.

After selecting an effective solution, it can be implemented in a next-generation redesign, or if it can be realized in software, as an update for fielded products. TPUI-based simulations will mostly facilitate redesign or designing variations on existing designs. After all, the usage-related input signals to the original simulation model must also be meaningful in a modified model. If the hinged door of a refrigerator is replaced by a sliding door or a lid, the collected door data are likely no longer meaningful.

12. FUTURE WORK

Up till now, we have applied several simplifications and shortcuts in our simulations, which we applied to a limited set of units. We could think of several options to further improve the realism and the usefulness of TPUI-based simulations. Among other things, it seems worthwhile to consider and investigate:

- influence of usage phenomena such as environment temperature, quantity and temperature of items put in and taken out.
- inclusion of physics effects currently ignored in the model, such as heat exchange between compartments, energy consumption by the light, interior geometry, etc.
- fine-tuning model parameters by comparison with a physical specimen of the refrigerator – which is up to the company, and which might not lead to publishable results due to confidentiality issues
- spreading multiple openings during an hour evenly or randomly over that hour
- more fielded units, and to apply machine learning to simulation results with more features from the data to create faster-computing models for investigating the influence of door openings.

Finally, in the context of generalization, it would be interesting to investigate how TPUI-based simulation can be applied to other products and how these may benefit from it. Perhaps our approach of customizing simulation elements to allow variations of values that are normally considered to be fixed will turn out to be generally applicable solution for introducing human manipulations into engineering simulations.

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