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Simulations Based on Product-Usage Information From Connected Products to Support Redesign for Improved Performance: Exploration of Practical Application to Domestic Fridge-Freezers

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The real-life use of a product is often hard to foresee during its development. Fortunately, today's connective products offer the opportunity to collect information about user actions, which enables companies to investigate the actual use for the benefit of next-generation products. A promising application opportunity is to input the information to engineering simulations and increase their realism to (i) reveal how use-related phenomena influence product performance and (ii) to evaluate design variations on how they succeed in coping with real users and their behaviors. In this article, we explore time-stamped usage data from connected fridge-freezers by investigating energy losses caused by door openings and by evaluating control-related design variations aimed at mitigating these effects. By using a fast-executing simulation setup, we could simulate much faster than real time and investigate usage over a longer time. We showed that a simple, single-cycle load pattern based on aggregated input data can be simulated even faster but only produce rough estimates of the outcomes. Our model was devised to explore application potential rather than producing the most accurate predictions. Subject to this reservation, our outcomes indicate that 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 more energy-efficient ways of dealing with door openings. Based on our findings, we discuss possible impacts on product design practice for companies seeking to collect and exploit usage data from connected products in combination with simulations.
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1 Introduction

1.1 Utilizing Time-Stamped Usage Information From Connected Product in Prescriptive Analytics. Product usage information (PUI) can be considered a valuable source of knowledge for predicting usage and behaviors of current and future products. Traditional ways of collecting PUI include observation of human subjects, conducting user surveys, and taking interviews [1]. Also, researchers have instrumented product units that are already owned by users with sensors and communication units to collect information [2,3]. However, now that information-collection capabilities and connectivity are increasingly becoming standard features of products, it becomes even easier for manufacturers to obtain PUI [4], so that users of the same product can be compared with each other.

In the FALCON project funded by the European Union (2015–2017), we have investigated opportunities to exploit collected data from connected products in several ways. The main deliverable of the project was a "virtual open platform" to collect and process data generated by connected products and related social media, with the objective to extract actionable knowledge to be used as input for (re)design of products and related services [5]. This article describes a study conducted in the context of FALCON that aimed to report on, and implement, simulations based on time-stamped PUI (TPUI)—i.e., each data sampling holds information about the time of usage or nonusage. The virtual open platform offers 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 module called PUI query builder [5].

According to Porter and Heppelmann [4], the transformation from PUI to knowledge or, as they call it, insight, can be achieved by applying *data analytics*, which manifests at various levels of sophistication, namely, (i) descriptive, (ii) diagnostic, (iii) predictive, and (iv) prescriptive. In the literature on data analytics, simulation is considered to be one of the pillars to support the highest sophistication level, i.e., prescriptive analytics [6,7]. One of the business processes where prescriptive knowledge can be deployed is in design. Simulations can also be used just for predictive

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analytics, for instance, predicting when a particular part in a particular fielded unit will be worn out—but the potential prescriptive[1] power lies in the capability to evaluate design alternatives by modifying the simulation model and thus generate actionable knowledge from TPUI. The term "actionable" expresses that the knowledge is supposed to provide insight in how, given the actual usage, the product's design can be improved in terms of performance, which can refer to any output measure that determines the quality of the product's functioning. Examples of performance indicators are speed of operation, supplies consumption, noise production, and quality of product outputs.

1.2 Testcase Product: A Domestic Fridge-Freezer. From the companies participating in FALCON, various products equipped with information collection capabilities were available. A fridge-freezer produced by consortium partner Arçelik, a consumer electronics and household appliance manufacturer based in Turkey, was selected for demonstrating the potential of TPUI-based simulation. We based our choice primarily on two requirements. Obviously, a key requirement for the product to be used as a simulation testcase is that the collected information should cover aspects of use by human users or operators. The second requirement was that it could reasonably be expected that the simulations would produce actionable knowledge pertaining to the product's design. To that end, our reasoning has been that dynamic simulation with TPUI as input can only produce actionable knowledge if the investigated performance measure of the product (i) is quantifiable from the simulation results, (ii) is influenced by the timing of changes in the TPUI, and (iii) design modifications can be conceptualized of which the influence on performance can be tested through simulation.

As prerequisite (i) suggests, some performance measures are not quantifiable based on simulation results. This is for instance the case if a performance measure is subjective, such as the taste of coffee produced by a coffee maker. Concerning (ii), for many products the available TPUI is likely to represent the type, intensity, and timing of user interactions. If, for instance, we consider a washing machine—another product from which TPUI was available in FALCON—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. To allow performance assessment, simulation only needs user-interaction related input parameters 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 allowing investigation of effects on a large time scale, such as seasonal influences on program selection, time stamps have no added value.

Contrarily, in the case of a fridge-freezer, there is direct interplay between, on the one hand, user interactions with its doors and its contents and, on the other hand, the part of product operation that determines performance, i.e., its continuously ongoing refrigeration cycle. In this case, we need to consider use interactions *with their timing* as simulation input, because the distribution of consecutive openings over time is likely to have influence on their overall effect on energy consumption.

[1]Interpretation of the term "prescriptive analytics" remains somewhat fuzzy, and the suggestion that it is supposed to correspond to a high level of refinement can be disputed. Admittedly, our implementation does not produce a direct what-to-do recommendation. Instead, the prescriptive effect of simulations is indirect: the simulation results have to be interpreted, and humans have to prepare the alternative designs for evaluation. On the other hand, there are very direct ways of using analytics prescriptively that are hardly sophisticated: consider for instance a sensor able to detect part failure in association with a straightforward rule "IF part failed THEN arrange to have part replaced."

Regarding prerequisite (iii), we identified three control-related design variations that influence the fridge-freezer's performance in terms of energy consumption. The investigated fridge-freezer is equipped with fans that are supposed to improve heat exchange in the compartments. It can be expected however, that when the door is open, a fan will stimulate heat exchange with the warmer air outside, which can possibly be mitigated by additional control of the fan or by leaving out the fan. Thus, the three design variations that we decided to compare by exposing them to real usage information are as follows: (i) no fan, (ii) a fan that is controlled based on compressor activity only, and (iii) a controlled fan that also switches off if the door is open.

1.3 Structure of the Article. This article elaborates on a paper we presented at the ASME-CIE 2018 conference [8] and is structured as follows. In Sec. 2, we report on related work: first, on simulations with data and second, on energy consumption of fridge-freezers, and how it is influenced by usage. Next, in Sec. 3, we present our research approach, including considerations regarding data collection and sampling, as well as our simulation approach and validation approach. The results are presented in Sec. 4, where we discuss outcomes in terms of performance of fridge-freezers and the influence of user actions, the simulation performance and the utility of TPUI-based simulations. Finally, in Sec. 5, we present our conclusions and discuss what could be done next.

2 Related Work

2.1 Simulation With Data From Connected Products. Shannon [9] defined simulations experiments with input–output models of real systems in order to predict probable future output for a given input, to understand system behavior and/or to evaluate operation strategies, pointing 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, mathematical models fall short in capturing certain other involved processes, such as human activity or the weather. This is where sometimes makeshift models are applied, introducing artificial input signals based on assumptions or aggregations from user observations, such as repetitive cyclic load patterns (e.g., Refs. [10] and [11]). Instead of using such potentially questionable inputs we propose to use the real-life TPUI that is increasingly becoming available from connected products.

A concept related to TPUI-based simulation is *data-driven simulation*, where data not only corresponding to the inputs to the simulation model (e.g., human interactions) but also real-life data corresponding to simulation outputs is used, with the goal to optimize the simulation model in terms of accuracy (e.g., Ref. [12]). The concept of *digital twins* goes beyond this by realizing a two-way connection: it aims to implement real-time adaptation of the product (in particular through maintenance) based on the simulation forecasts [13,14]. Digital twins focus on monitoring of individual product units, which are typically capital goods such as aircraft [15], whereas TPUI-based simulation includes analysis of the use of multiple units as it is typically important in the case of consumer products. Unlike data-driven simulation or digital twins according to these interpretations, it does neither include runtime improvement of the simulation model nor interventions during operation of individual units.

In the case of TPUI-based simulation, real-life data are only used as simulation *input*, while the simulation model itself is assumed to be sufficiently realistic. Hence, it is assumed that the simulation results, can be used to (i) evaluate the performance of the product under 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 alternative designs in the form of variations on the simulation model, based on real inputs.

In our focus area, simulations with consideration of human inputs, interactive simulations with real humans in the loop have been put forward to increase realism (e.g., Refs. [16] and [17]). Just like hardware-in-the-loop simulations, where the hardware, or part thereof, is physical rather than virtual, these have the drawback that they must run in real time and cannot be accelerated to investigate usage over longer time intervals [18]. Moreover, user testing is known to be expensive [19]. 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 [20], without the need to recruit human subjects and slow down to real-time execution. Similarly, realistic inputs can also be obtained from observation of human users (e.g., Ref. [21]), but today's connected products provide the opportunity to automate this process and have new data reflecting changes in user's behaviors over time immediately available.

Our literature search revealed that in most other reports on product simulations with TPUI, also output data were processed in a data-driven simulation setup, and the focus was on optimizing models—particularly discrete-event simulation models of manufacturing systems [22–24]. Others have conducted simulations based on PUI in a descriptive-analytics setup, with the aim to assess performance of products or product instances with no feedback loop to design: Gonder et al. [25] used location data from instrumented electric vehicles to obtain realistic energy consumption values from simulations, and Urban and Roth [26] simulated smart thermostats together with air conditioner systems based on mainly static PUI, such as temperature set-points, collected from end users to compare the performance of different types of thermostats. Goyal et al. [27] simulated distribution transformers in power networks based on data collected from smart meters in end users' homes to support predictive maintenance. In this case, the simulated products were not the products providing the TPUI.

One example where some prescriptive feedback to design was realized is the work by Pei et al. [3], who aimed to improve electronics packaging. They did not only compare and optimize data-driven simulation models of degradation based on TPUI from 100 units of an unspecified mobile computing device but also used the simulation results to derive more realistic requirements for next-generation designs. However, they did not perform what-if studies with design variants.

2.2 Energy Consumption of Fridge-Freezers. The fridge-freezer is known to be one of the largest electricity consumers in households. Typically, refrigerators and freezers are on all the time [28], and domestic refrigeration is considered responsible for 4.5% of the total global electricity consumption [29], for about 12% of residential electricity consumption in Australia [30] and for 33.6% of the total electricity consumption per household in the United Kingdom [31][2]. According to investigations by Biglia et al. [33] involving 483 fielded fridge-freezers, an average unit consumes 390 kWh/year with the freezer compartment set at –20.3 °C (–4.5 °F) on average and the cooler compartment at 5.3 °C (41.5 °F).

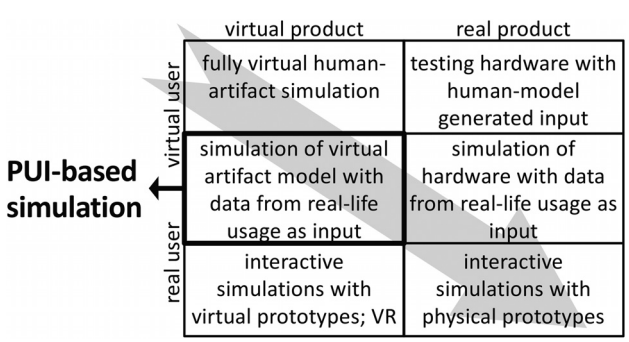

Fig. 1 Filling the gap between virtual-user input and real-user real-time input (arrow depicts increasing realism)

The frequency and duration of door openings are known to have influence on a fridge-freezer's thermodynamic performance and energy consumption [34]. On the one hand, there are authors who point out that other use-related factors, such as temperature setting and room temperature are more influential [29,35], on the other hand, several sources reviewed in Ref. [36] claim that with other factors constant, door openings are reported to increase energy consumption by 1–8%. Thus, considering the aforementioned percentages reflecting the contribution of refrigeration appliances to overall electricity consumption, reducing the influence of door openings can have a large impact. Experiments with installed refrigeration units as well as simulations have also been conducted to investigate the influence of door openings. Sarmah [37] applied several variations of cyclic door-opening patterns to a refrigerator and reported up to 113% increase in energy consumption for a somewhat unrealistic pattern where the door was open 1/3 of the time. Simulations have been deployed, for instance, in Refs. [38] and [39], also based on cyclic patterns rather than on data collected from real usage.

3 Research Approach

3.1 Data Collection, Sampling Considerations and Statistical Analysis. The original data produced by Arçelik's connected fridge-freezers contains time-stamped values of readouts from various sensors. The defaulted interval between successive readouts is $t_{\text{sampling}} \approx 1\,\text{h}$. Among these are (i) the end time of the interval (the time stamp), (ii) the total door opening times for the fridge compartment and freezer compartment, and (iii) the numbers of door openings during the elapsed interval.

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 $(t_{\text{transfer}} - t_{\text{sampling}}, t_{\text{transfer}}]$ the door has been open n times for the cumulative duration

$$\Delta t_i(t_{\text{transfer}}) = \sum_{k=1}^{n} \Delta t_k \tag{1}$$

with the individual Δt_k not specified in the data, we have simulated that, starting at t_{transfer}, the door was open for $\Delta t_i(t_{\text{transfer}})$. 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 $\Delta t_i(t_{\text{transfer}}]$ is no longer cumulative, would enable us to simulate the actual door openings.

In principle, more accurate input can already be generated from the currently available data by randomly distributing n door openings over the interval $(t_{\text{transfer}} - t_{\text{sampling}}, t_{\text{transfer}}]$. However, this would introduce additional processing steps that are eventually not needed once event-based data collection has been implemented. Although, for now, it will produce less accurate outcomes due to disregard of the expected nonlinear temperature effects after each door opening[3], we have assumed that the workaround to use hourly accumulated door openings as the actual data will not influence our assessment of the added value that TPUI can offer in evaluation of design decisions.

[2]The discrepancy between the last two figures can possibly be explained by the fact that air conditioners are more commonly used in Australia than in the UK [32].

[3]The average for n for those intervals where $n > 0$, in the data from all the fridge-freezer units, is around two for both compartments, i.e., mostly the door has been open twice. This corresponds to ignoring nonlinear effects from one additional opening per opening that was considered.

The data that we used was collected from 43 fielded fridge-freezer units during 432 days. The total number of samplings over all units was 67,234, but upon closer inspection several irregularities of three particular types were revealed: (i) 7826 samplings turned out to be duplicates, (ii) another 5847samplings were taken less than an hour after the previous sampling, often reporting the same data, and (iii) 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 samplings reporting zero door openings—we have assumed that they were caused by connectivity problems. To be able to further characterize the data, we deployed RAPIDMINER data-mining software to remove all duplicates and samplings reporting at less than an hour or more than a day after the previous one. We also removed the five units that had been in use for less than three days, while all other units had been in use for more than six days. In the remaining data set from 35 units, the data-collection time span per unit ranged from 6.2 to 160 days. Our assumption has been, that data from longer time intervals provide more complete insight in the use patterns, because they are likely to include effects of seasonal changes and absence due to, for instance, vacations.

Applying judgmental sampling [40], we selected nine units that covered a reasonable spread over the daily open durations and number of openings, and for each, selected the longest possible contiguous interval of samplings that did not contain gaps of more than a day. We compared the freezer data from our selected units *A–J* (letter *I* omitted to avoid confusion) to the preselected population of 35 units based on the following statistical descriptors: (i) time interval covered by all the samplings in days, Δt_{tot}, (ii) average number of door openings per day, $\overline{f}$, (iii) average time[4] per door opening in seconds, $\overline{\Delta t_i}$, (iv) its standard deviation $\sigma(\overline{\Delta t_i})$, (v) average door-open time per day in seconds, $\overline{\Delta t_{\text{daily}}} = \Sigma \Delta t_i / \Delta t_{\text{tot}}$, (vi) average interval between openings, $\overline{\Delta t_{ij}}$, and (vii) its standard deviation $\sigma(\overline{\Delta t_{ij}})$. We did this for both the total set of samplings from each unit *A–J* and for the subset selected as simulation input (for unit *D* the subset is identical to the total set). The result is visualized as histograms in Fig. 2, and the most important average values are compared in Table 1. The histograms suggest that the selected samplings reasonably cover the same ranges as the preselected 35 units do, but the averages in Table 1 reveal a bias toward more openings and a longer opening time per day in the simulated samples. To express this bias, we have included a "door-openings exaggeration factor" for $\overline{f}$ and $\Sigma \Delta t_i / \Delta t_{\text{tot}}$ that will have to be considered in generalizing the outcomes.

3.2 Simulation Approach. For simulation modeling and execution, we deployed MATLAB/SIMULINK, as it is widely used for engineering simulations [41,42], and provides a basic refrigeration model that we could adapt and extend for use in our investigations. Figure 3 shows our simulation model of the fridge-freezer. It is based on a refrigeration model provided with SIMULINK (*Refrigeration cycle model […]*) [43], which was modeled using Simscape, SIMULINK's physical-systems modeling environment. 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 product design. Assuming that door-opening behaviors in using fridge-freezers do not depend on the particular make of the appliance, our investigations in this article can be said to apply to a hypothetical fridge-freezer design and variations on it. This way, we also did not have to expose company-confidential design information.

[4]Cumulative times per sampling as in Eq. (1). The TPUI also contained several door openings of zero seconds, which we ignored in counting the number of door openings. Inclusion of these in Ref. [8] explains some differences in the results presented here.

To consider the effect of door openings we applied modifications and extensions, the most important ones of which are (names in *italics* refer to block names in Fig. 3) as follows:

(1) Adding (i) a *TPUI data import* block to import the CSV file using the "signal builder" and (ii) stateflow decision logic *interpolation removal* to remove meaningless interpolated values that the signal builder adds between entries in the CSV file.
(2) Adding a *manual override* to allow interactive checking of the effect of door openings and activating a reference simulation during which the door is always closed. It consists of two manual switches, which can be operated by the simulation user, even while the simulation is running. To use the TPUI data, the *source selector* switch is set as shown. In the other position, the simulation interactively receives its door openings from the *door opened/closed* switch. To run the reference simulation with zero door openings, the manual input is permanently set to its "0" port.
(3) Modification of the Simscape model of the *compartment* of the fridge-freezer. The compartment model from Ref. [43] was altered by including stored items, by adding a fan and by implementing the influence of door openings on heat exchange. The fan (if present) reacts to compressor activity and, depending on the design variant, to door openings. In accordance with the fans in Arçelik's fridge-freezer, a constant 3 W is added to the power consumption if it is on. Influence of door openings and the fan on heat exchange was implemented by including modified Simscape blocks representing heat conduction and convection—which normally have fixed parameters (coefficients and/or surface areas)—so that they could receive varying parameters based on door-openings and activity of the fan. Table 2 shows the logic of changing heat-exchange parameters at the evaporator, inside the interior (air), through the door (if closed) and outside (air). We optimized the positive influence of the fans by applying fine-tuned delays to the synchronization with the compressor.
(4) Adapting values regarding dimensions, etc., to values corresponding to those of a typical household fridge-freezer.
(5) Creating outputs to allow assessment of our performance measures (i) energy consumption by the compressor and the fan *(energy, numeric)*, and (ii) *average temperatures* inside the compartment as well as *output graphs*.
(6) Adding a subsystem *performance computation*, mainly to compute the performance of the simulation itself according to Eq. (2), as well as elapsed and remaining simulation time.

Figure 4 shows an example of typical graphical output of the simulations. 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 operating the switch in Fig. 3. Figure 4 shows the course of the temperature in the compartment, as well as the temperatures of already-cold food and power consumption. 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 fridge-freezer. Since this is a one-time event that does not apply during steady-state use, we have eliminated its influence by ignoring the first 8000 s of each simulation run.

The actual fridge-freezer from which the data was collected uses one compressor for both compartments. We simplified this setup by running separate simulations for the fridge and the freezer, each with their own door-opening data and set temperatures (4 °C and −18 °C, respectively), and, where applicable, merged the results afterward. Consequently, we also did not consider heat exchange between the two compartments. We have assumed that the fridge-freezer was situated in a kitchen with room temperature 23 °C (73 °F). The three design variations specified in Sec. 1.1, each applied to the two compartments, provided

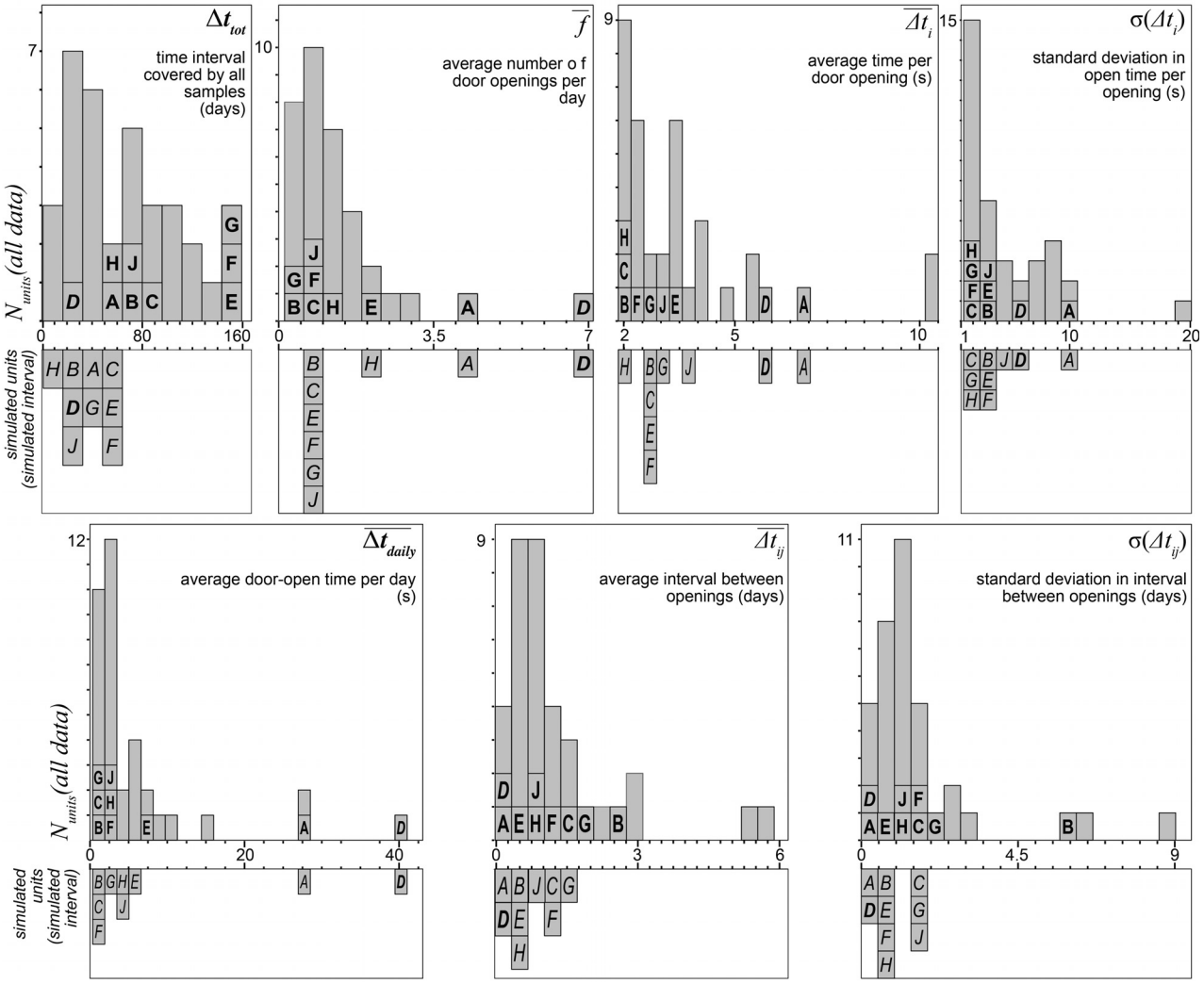

Fig. 2 Statistics of collected and selected fridge-freezer data

six what-if alternatives to be simulated, and to be combined to represent the fridge-freezer as a whole.

3.3 Validation Approach and Hypotheses. To validate the utility of simulating based on TPUI, we have compared it with conventional simulation of product usage based on a cyclic load pattern defined by average values, as was for instance used in in Refs. [11], [38], and [39]. Such load patterns, that can be created from aggregated PUI, can be advantageous if they provide the same outcomes in the much shorter simulation time that they require. Thus, we formulated the following hypothesis: *Simulations based on cyclic load patterns derived from average values cannot be used to obtain the same outcomes in less time*. Our assumption is that the irregularities in the real use patterns, absent in repetitive identical door openings, will lead to different outcomes thus underpinning the added value that TPUI-based simulation offers over cyclic load patterns, where, ideally, a fast simulation result over a longer time of usage Δt_{tot} can be obtained by simulating just one cycle—representing the average time $\overline{\Delta t_{ij}}$ between two openings—and multiplying the outcomes by a factor $\Delta t_{\text{tot}}/t_{\text{cycle}}$.

Rather than to create faster or more accurate or simulations of fridge-freezers, our objective was to validate the added value of real-life TPUI as simulation input to support evaluation of design decisions. Yet, to achieve added value we considered it important that simulations could be executed reasonably fast and that the results are sufficiently correct to be realistic. Therefore, we performed a basic assessment of these aspects.

Table 1 Statistical comparison between population of 35 units and selected units (freezer compartment)

	$\overline{f}$: average number of door openings /day	$\Sigma\Delta t_i/\Delta t_{\text{tot}}$: average door open duration/day (s/day)	$\overline{\Delta t_i}$: average open-time per opening (s)	$\overline{\Delta t_{ij}}$: average time between openings (days)	$\sigma(\overline{\Delta t_i})$ (s)	$\sigma(\Delta t_{ij})$ (days)
Population average (35 units)	1.15	4.32	3.55	1.43	4.59	1.76
Sample average (units A–J)	1.34	5.82	3.07	1.27	3.45	1.88
Sample average (simulated interval of units A–J)	2.09	9.99	3.60	0.80	4.34	0.92
Door-openings exaggeration factor in simulated samples	1.82	2.32				

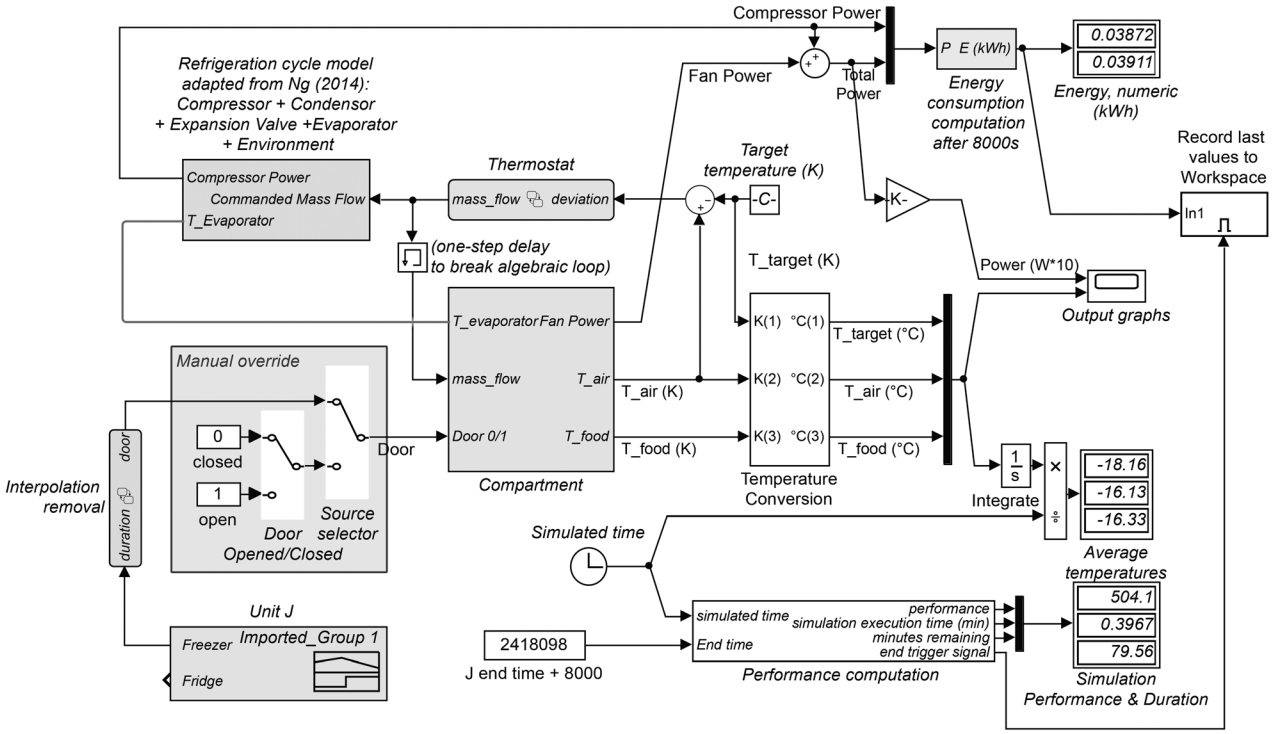

Fig. 3 Fridge-freezer simulation mode

Table 2 Influence of door openings on heat transfer mode

		Heat transfer			
Door	Fan	Evaporator	Interior	Door	Outside
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[a] and convection[b]	Infinite convection[b]
Open	On	Forced convection	Infinite convection[b]	Infinite conduction[a] and convection[b]	Infinite convection[b]

[a]Enabled by reducing area in variable-conduction block to include only walls, bottom and top.
[b]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).

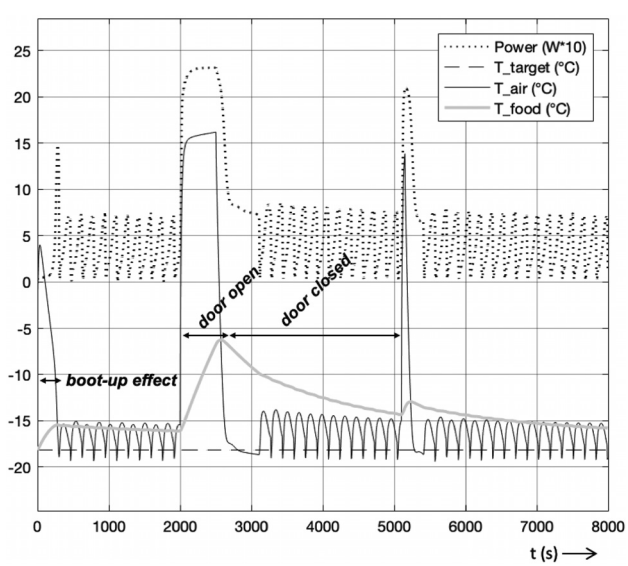

Fig. 4 Simulation output with annotations

To assess the speed of simulations, we measured the *simulation performance*. According to Ref. [18], where it was applied to unrelated other simulations, simulation performance can be defined as

$$p_{\text{sim}} = \frac{T_{\text{virtual}}}{T_{\text{sim}}} \tag{2}$$

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 $p_{\text{sim}} > 1$ indicates a performance p_{sim} times faster than real-time.

For a basic verification of the correctness of the simulations, we have compared the overall energy consumption to values from literature, and, in relation to the considered door openings and design variations, formulated the following expected outcomes: (i) a fan active in a closed compartment improves heat exchange when the evaporator is active, and therefore reduces energy consumption, (ii) door openings increase energy consumption, and (iii) a fan active in an opened compartment will lead to even more energy consumption than is caused by the open door alone. These expectations are based on common knowledge available from refrigeration literature cited in Sec. 2.2. Thus, we expect our three design alternatives to rank as follows: with all other factors equal,

the design with no fan consumes the most energy, followed by the design in which the fan is controlled based on compressor activity (provided that the door is closed most of the time), and then the variant with fan that is also switched off when the door is open. Note that these expectations just predict rankings of design alternatives and situations for verification purposes and do not predict the magnitudes of the differences.

4 Results and Discussion

4.1 Fridge-Freezer Performance and Influence of Door Openings. Focusing on the freezer compartment, which consumes the bulk of the power, Fig. 5 shows our simulation outcomes. The relative influence d of door openings on the energy was calculated as a percentage (right-hand side), based on comparing a simulation with TPUI input with the reference simulation in which the door was always closed. In the reference simulation with closed door the energy consumption is 0.87 kWh/day, which is reduced by 0.02 kWh/day with a fan (both variants). In Figure 5, the units are ordered based on the value for d in the two cases where a fan is employed.

The relative influence d of door openings appears to increase consistently if, comparing the same fan-control alternative in two units, both the average daily frequency $\bar{f}$ of door openings and the average daily opening duration $\overline{\Delta t_i}$ increase. There appears to be no consistent relation if only one of the two descriptors increases.

For three units we have also simulated the use of the fridge compartment. The results are shown in Table 3, together with the consequences for the fridge-freezer as a whole. In the reference simulation, the fridge compartment consumes considerably less than the freezer, namely, 0.057 kWh/day (only 6.6% of the freezer consumption), which is reduced by 0.002 kWh/day with a fan. As expected, in all simulations, the design alternatives without fan consistently showed the highest energy consumption, and the ones with fan controlled by both the compressor and the door the lowest.

In all investigated cases, the relative influence (%) of door openings d is larger in the fridge compartment than in the freezer, and, on the other hand, the absolute influence (kWh) is larger in the freezer. The largest relative influence, namely about 15% increase of energy consumption caused by door openings, could be seen in the case of a fan controlled by the compressor only, in the fridge compartment. This is an unlikely design choice (and therefore not included in Table 3), since practically every fridge-freezer has lighting in its fridge 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. However, unlike the Arçelik fridge-freezers from which we collected data, many fridge-freezers have no door switch for lighting 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 being evaluated and that, of all remaining options, shows the largest absolute impact of door openings on energy consumption.

Based on the computed daily consumption rates, the yearly energy consumption turns out to be in the range of 330–340 kWh/year. Considering that the investigated fridge-freezer is a recent model, and that average energy consumption values from the literature typically include older units [34,36], while energy savings advance with every next generation of refrigeration appliances [44], this appears to be consistent with the 390 kWh/year from Ref. [33] with the average freezer set at 2.1 °C colder than in our simulation and the average fridge compartment at 1.5 °C warmer.

The average temperatures that were computed in the simulations revealed differences between the design variations with and without fan. Without fan, the air and the food items averaged at 1.5 °C warmer than the set temperature in the freezer compartment and 0.4 °C colder than the set temperature in the fridge compartment. Using a fan consistently resulted in a 0.2 °C and 0.4 °C higher average temperature, respectively. The air temperature curve in Fig. 4 clarifies how the average temperature does not necessarily correspond to the set temperature: the cycle is "asymmetric," with different areas above and below the set value. By lowering the set value for the fan-equipped varieties we could achieve the same average temperatures as for the fanless varieties. Although this increases energy consumption by about 1.3% for the freezer and 3.6% for the fridge compartment, the fan-equipped varieties still prove to be more energy efficient.

Based on our findings, we could assess some of the statements regarding influence of door openings that we cited in 2.2. It turns out that when the doors are being opened rather frequently, the lower end of the 1–8% range mentioned in Ref. [36] is reached, but only if the freezer compartment has a fan that does not react to door openings. In the corresponding design variation in our simulations, door openings had a 0.138–1.43% impact on energy consumption. In these cases, it might be worthwhile to consider adding a door switch to control the fan or not to have a fan in the freezer compartment.

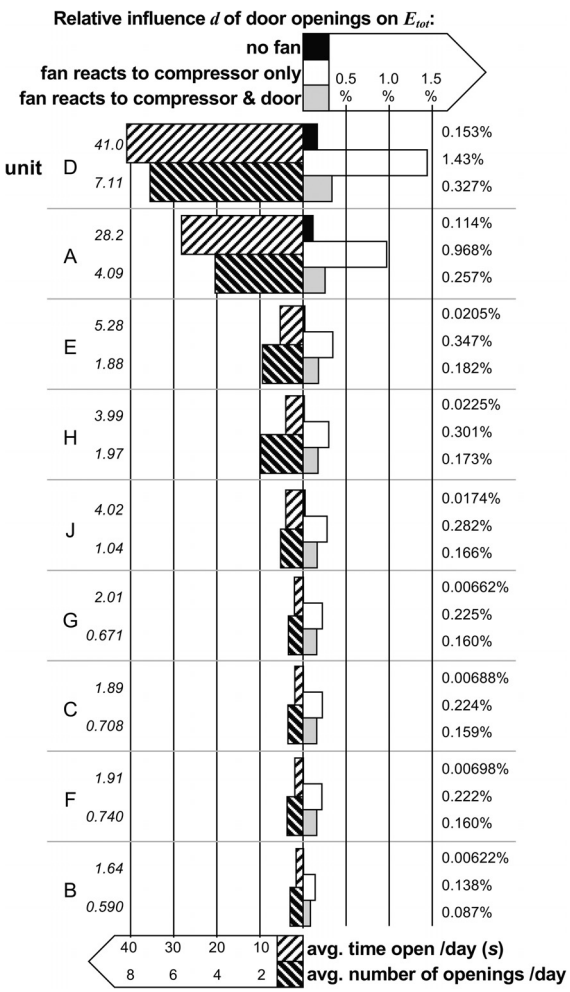

Fig. 5 Overview of simulation outcomes (freezer compartment)

4.2 Simulation Performance. To conduct the simulations, we relied on hardware with a level of processing power that is easily accessible within typical engineering environments[5]. Overall, simulation performance according to Eq. (2) was between 1500 and 1900 times real-time. We could not find any evidence that having to import and process TPUI would slow down the

[5]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.

Table 3 Simulation outcomes including fridge compartment

Unit		*A*		*D*		*G*	
Average daily fridge compartment open duration, s (simulated interval)		**101.4**		88.0		***19.4***	
Average daily fridge compartment open frequency (simulated interval)		**9.9**		6.3		***2.7***	
		Fridge compartment	Both compartments	Fridge compartment	Both compartments	Fridge compartment	Both compartments
Influence *d* of door openings on energy consumption	No fans	1.75%	0.22%	**3.89%**	**0.38%**	***0.40%***	***0.03%***
	Freezer fan controlled by compressor only, fridge fan controlled by compressor and door	1.66%	1.01%	**3.2%**	**1.54%**	***0.35%***	***0.23%***
	Both fans controlled by compressor and door	1.66%	0.34%	**3.2%**	**0.50%**	***0.35%***	***0.17%***

Note: Maxima in **bold**, minima in ***bold italics***.

simulations. Although the fast simulation execution allowed us to investigate use over a longer time interval, an average simulation run still took around 30 min. For each unit, five runs were needed to consider the three design variants (each variant responds differently to door-opening data but the two fan-equipped ones behave the same if the door remains closed) for the freezer and five more for the fridge, plus additional runs as discussed in Sec. 4.3. The total time needed per unit limited us to investigating both fridge-freezer compartments of only three units, and just the freezer—which has the largest impact—of six additional units.

4.3 Utility of Time-Stamped Product Usage Information-Based Simulations. To test our hypothesis that there would be no gain in replacing the real time-stamped usage data input by equivalent cyclic door-opening patterns, we have created repetitive patterns for the freezer compartment as described in Sec. 3.3. We did this for four of the units, *A*, *B*, *D*, and *J*, which according to Fig. 2, together offer a reasonable coverage of the various intensities of door-opening activity, and for all three design variations, i.e., 12 simulation runs. To compare the results, we computed both the absolute aberration $\Delta d_{\text{abs}} = |d_{\text{cyc}} - d_{\text{TPUI}}|$ and the relative aberration $\Delta d_{\text{rel}} = |d_{\text{cyc}} - d_{\text{TPUI}}|/d_{\text{TPUI}}$, both expressed as percentages—with d_{cyc} the value obtained based on the cyclic pattern and d_{TPUI} the value obtained from the original simulation based on TPUI.

Since the real advantage of simulation with cyclic patterns lies in the time savings that can be achieved by simulating just one cycle with one door opening, to be taken as representative for any—longer—time span, we executed the 12 runs for just one cycle. Simulating the longest cycle among the units *A*–*J* takes about 1 min, and the longest cycle in the whole population of 46 units takes about 6 min to simulate with the performance rates mentioned in Sec. 4.2.

Comparing the 12 single-cycle simulation runs for units *A*, *B*, *D*, and *J*, we found that the absolute aberration ranged from $0.008\% \leq \Delta d_{\text{abs}} \leq 0.173\%$, averaging at $\overline{\Delta d_{\text{abs}}} = 0.071\%$, and the relative aberration compared to the results obtained from TPUI ranged from $1.50\% \leq \Delta d_{\text{rel}} \leq 388\%$ averaging at $\overline{\Delta d_{\text{rel}}} = 71.2\%$ (Table 4, first four result columns). All combinations of units and design variations showed similar values for Δd_{abs}, and consequently, if the resulting value of d is low, the value of Δd_{rel} becomes large, i.e., the increase predicted based on one cycle can be almost four times higher than the increase based on TPUI input.

It seemed likely that our simulation results were influenced by interference between door-opening cycles and the compressor on-off cycle, which have periods in the same order of magnitude, i.e., 100 s–1000 s of seconds. To mitigate the influence of the compressor on-off cycle, we have, therefore, repeated all simulations of units *A*, *B*, *D*, and *J* with door-opening times shifted over half the compressor cycle time, and averaged the outcomes among each pair of shifted/nonshifted simulations, thus obtaining a value $d_{\text{mitigated}} = (d_{\text{nonshift}} + d_{\text{shift}})/2$, with d_{nonshift} the value obtained without, and d_{shift} the value obtained with the shift in door-opening times. To quantify the influence of the interference, we first computed both the absolute aberration $\delta d_{\text{abs}} = |d_{\text{shift}} - d_{\text{nonshift}}|$ and the relative aberration $\delta d_{\text{rel}} = |d_{\text{shift}} - d_{\text{nonshift}}|/d_{\text{nonshift}}$, both expressed as percentages.

Expectedly, shifting door-opening times had less influence on the original TPUI-based simulations ($0.000\% \leq \delta d_{\text{abs}} \leq 0.034\%$, $\overline{\delta_{\text{abs}}} = 0.007\%$; $0.011\% \leq \delta d_{\text{rel}} \leq 63\%$, $\overline{\delta d_{\text{rel}}} = 8.47\%$) than on the single-cycle simulations ($0.000\% \leq \delta d_{\text{abs}} \leq 0.228\%$, $\overline{\delta_{\text{abs}}} = 0.062\%$; $4.06\% \leq \delta d_{\text{rel}} \leq 270\%$, $\overline{\delta d_{\text{rel}}} = 49.5\%$). Besides, we also found an indication that, for the single-cycle simulations, the compressor on-off cycle influences even the outcomes of the reference simulations (no door openings), probably due to the shorter time span being simulated: whereas the longer reference simulations of the TPUI-based simulations consistently showed a ratio of 1.0274 when comparing energy consumption with and without fan, the same ratio varied between 1.0261 and 1.0272 for the reference simulations of the single-cycle investigations.

Considering the fact that the on-off cycle of the compressor can have any arbitrary offset in time, we have assumed that the value of $d_{\text{mitigated}}$ for the TPUI-based simulation provides the best assessment of the influence of door openings. Once again we computed the values for Δd_{abs} and Δd_{rel} to compare values of $d_{\text{mitigated}}$. It turns out that a value obtained from single-cycle simulations shifted over time slightly improves the assessment of the influence of door openings based on one averaged cycle: comparing the 12 values for $d_{\text{mitigated}}$ from single-cycle simulations with the ones from simulations based on TPUI, we found that the absolute aberration ranged from $0.003\% \leq \Delta d_{\text{abs}} \leq 0.154\%$, averaging at $= 0.054\%$, and the relative aberration ranged from $3.89\% \leq \Delta d_{\text{rel}} \leq 263\%$ averaging at $\overline{\Delta d_{\text{rel}}} = 49.2\%$ (Table 4, right-hand part).

These findings appear to support our hypothesis: at least if predicting small increases in energy consumption, either due to the door-opening intensity or due to the design variant, the results from single-cycle simulations show unacceptably high relative aberrations. However, to get a first impression whether d is, for instance, in the 0.01% or the 1% range, running single-cycle simulations seems to make sense.

One likely cause of the inaccuracy of single-cycle simulations is interference with the compressor on-off cycle: after all, for just one cycle, the outcomes will more strongly depend on how, in time, a door opening is situated in relation to the compressor cycle. Over a longer simulation time with multiple repetitive door-opening cycles, variations caused by this effect may average out unless the door-opening cycle time happens to be a multiple of the compressor cycle time. We did perform some additional

Table 4 Simulation of freezer compartment: comparison between real usage data and cyclic door-opening pattern (one cycle only)

Unit	Design variant	d				$d_{\text{mitigated}}$			
		Based on TPUI	Based on one cycle	Δd_{abs}	Δd_{rel}	Based on TPUI	Based on one cycle	Δd_{abs}	Δd_{rel}
A	No fan	0.114%	0.174%	0.0597%	52.2%	0.117%	0.0993%	0.0173%	14.8%
	Fan controlled by compressor only	0.968%	0.851%	0.117%	12.1%	0.971%	0.817%	**0.154%**	15.9%
	Fan controlled by compressor and door	0.257%	0.159%	0.0977%	38.0%	0.259%	0.190%	0.069%	26.6%
B	No fan	***0.00622%***	0.0304%	0.0241%	**388%**	***0.00634%***	0.0230%	0.0166%	**263%**
	Fan controlled by compressor only	0.138%	0.238%	0.100%	72.3%	0.138%	0.237%	0.099%	72.0%
	Fan controlled by compressor and door	0.0872%	0.068%	0.0188%	21.6%	0.0838%	0.0654%	0.0184%	22.0%
D	No fan	0.153%	0.326%	**0.173%**	112.7%	0.154%	0.212%	0.058%	37.9%
	Fan controlled by compressor only	***1.434%***	**1.412%**	0.022%	***1.50%***	**1.432%**	**1.376%**	0.056%	***3.89%***
	Fan controlled by compressor and door	0.327%	0.289%	0.0384%	11.7%	0.327%	0.276%	0.051%	15.6%
J	No fan	0.0174%	***0.026%***	***0.008%***	47.4%	0.0228%	***0.0197%***	***0.003%***	13.6%
	Fan controlled by compressor only	0.282%	0.198%	0.085%	30.0%	0.299%	0.188%	0.111%	37.0%
	Fan controlled by compressor and door	0.166%	0.0541%	0.111%	67.3%	0.173%	0.0539%	0.119%	68.7%
	Average Δd			0.0712%	71.2%			0.0644%	49.2%

Note: maxima in **bold**, minima in ***bold italic***.

simulations with repetitive patterns over the full simulation time and still found values for Δd_{rel} of more than 300%. Moreover, these simulations would not offer any time savings, since we also found that using cyclic patterns does not improve the simulation performance. It is likely that by using the much more irregular TPUI data, interference with the compressor cycle is practically eliminated, as is evidenced by the small differences between the columns "d based on TPUI" and "$d_{\text{mitigated}}$ based on TPUI" in Table 4 (which is also why we have not updated Fig. 5 to reflect the values of $d_{\text{mitigated}}$).

This brings us to another possible reason for the differences in outcomes when comparing TPUI-based simulations with simulations based on cyclic patterns: possibly, the increase in energy consumption d depends not just on the average daily frequency $\overline{f}$ of door openings and the average interval between openings $\overline{\Delta t_{ij}}$ but also on other features hidden in less obvious characteristics of the TPUI (for instance, standard deviations of these values) or on characteristics of more complex regular patterns, such as concentrations of multiple openings in the morning and/or evening, or on weekends. In principle, it is for instance possible to identify such relations if we extract potentially interesting features from the original dataset, and experiment with machine-learning (ML) techniques to find combinations of factors that can predict simulation outcomes without running the simulations—after having performed TPUI-based simulations of several units with corresponding values of the candidate features to train the ML model.

With the features that we already extracted, one could for instance try to identify a single generalized relation expressing d as a function of uncorrelated statistical descriptors (see Sec. 3.1) as predictors, e.g.,

$$d = d(\overline{f}, \overline{\Delta t_i}, \sigma(\overline{\Delta t_i}), \overline{\Delta t_{ij}}, \sigma(\overline{\Delta t_{ij}})) \tag{3}$$

In a sense, this can be considered a metamodeling [45] or system-identification (cf. Ref. [46]) exercise, where a mathematical model is fitted to simulation inputs and outputs in order to replace the simulation. However, literature suggests that 10-15 observations per predictor variable (feature) are needed in order to avoid overfitting of the ML model [47]. With only 9 observations, we can hardly use only one of the features in Eq. (3), while, as argued above, the two features $\overline{f}$ and $\overline{\Delta t_{ij}}$ can probably not characterize the relation. This means that we need to run simulations with TPUI from a considerably larger number of units. Although the resulting ML model can be used to obtain fast predictions that replace further simulations, it applies to only one particular design variant, and it cannot directly be modified to represent and evaluate other design variants.

5 Conclusions and Future Work

In this article, we explored the use of TPUI-based simulations to assess the effect of user interactions and to review 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.

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 fridge-freezer 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 fridge-freezer is operating and consuming energy.

In the case of our fridge-freezer, the possibility to run simulations at 1500–1900 times real-time is indispensable to allow evaluation of design alternatives in a reasonable timeframe. We have investigated whether the TPUI can also be used to derive simple cyclic use patterns of which only one cycle needs to be simulated, which would make it possible to investigate a considerably larger number of units in less time. It turned out that a single-cycle pattern based on the average opening time per opening and the average time between openings can be used to get a first impression of the influence of door openings on the energy consumption. However, predicted increases in energy consumption that are well below 1% are subject to high error margins.

It is perhaps possible to construct more complex and more reliable single-cycle patterns if more features from the data are extracted and used, such as standard deviations of statistical descriptors and data reflecting the time of the day or the day of the week. In connection to the investigation of short single-cycle simulations, we found that interference with the compressor on-off cycle causes inaccuracies in the results. If our approach is generalized toward products other than fridge-freezers, one mandatory step in that approach should be to identify cyclic behavior and finding ways to mitigate it—e.g., by averaging simulations run at half the cycle time apart.

The increases in energy consumption as predicted by our simulations are by no means spectacular, indicating that the influence of door openings might be less than the consulted literature suggests. At any rate, considering the fact that domestic refrigeration appliances substantially contribute to the world's overall electricity consumption, even attempts to deal with the small influence of door openings that we found in our investigations could make sense, and we could demonstrate that, as design variant, having a fan in the freezer that does not react to door openings is not a good way to deal with user behaviors. This is particularly true for a small number (2 out of 9 in our simulations) of units that are subject to high door-opening intensities, leading to around 1% increased energy consumption. Since our sampling was biased toward more door openings by an exaggeration factor of about 2 (Table 1), a cautious estimate (also given the fact that devising the most accurate simulation model was not our primary goal) could be that an increase in energy consumption of around 1% due to door-openings occurs in 5–10% of all fielded refrigerators.

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 temperature, which might partly explain the differences with findings from field studies in the literature. With the sensing technologies currently implemented in fridge-freezers, it does not seem likely that such data can be added to the TPUI already collected [28]. Another factor resulting in larger energy-consumption increases could be the inclusion of older, less efficient refrigeration appliances in the field studies discussed in Ref. [38].

The possibility to exploit TPUI by performing simulations is likely to have impact on the way future products will be designed. Although we only investigated one type of product, we can provide some general recommendations based on the work presented in this article. First, 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 fridge-freezers, changes in ambient temperature are known to affect performance. Since the investigated fridge-freezers were not equipped with external temperature sensors, we could not investigate this effect. Moreover, if the product would keep track of its own energy consumption, simulations would no longer be useful for studying effects of user behavior on the current design—yet they would still add value if design alternatives are to be explored.

Second, once product units are out on the market, TPUI-based simulations can be used to study how real-life usage affects performance. If the data indicate that certain manifestations of usage negatively affect 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 redesign or, if feasible, in a software update for fielded products. TPUI-based simulations will mostly facilitate not-too-drastic redesign of existing products. After all, the usage-related input signals to the original simulation model must also be meaningful in a modified model. If the opaque compartment door is replaced by a transparent one, openings just for peeking inside will no longer happen, and the collected door data are likely no longer meaningful.

In the aforementioned product development scenario, the benefits gained from collecting and investigating TPUI, i.e., optimizing a future version of the product does not present any direct advantage to the end user. This alone will probably not justify having to pay extra for the connected product, and allowing it to consume bandwidth from the wireless home network. Therefore, we suggest that if a company wants to convince customers to buy connected products, it has to offer additional services that exploit the data in a way that is attractive to them—for instance, supporting analytics-based predictive maintenance (e.g., Ref. [48]). An alternative would be to not let the customer pay for the connectivity, and, for instance, to let the product transmit its data using an wireless phone connection with a subscription paid by the manufacturer.

Obviously, TPUI-based simulation is far from a mature approach. Up till now, we have applied several simplifications and shortcuts in our simulations, which we applied to a limited set of units of only one type of product. We could think of several options to further improve the realism and the usefulness of TPUI-based simulations. To start with, for the fridge-freezer 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. In addition, the model parameters can be fine-tuned by comparison with a physical specimen of the fridge-freezer. This is up to the company, and it might not lead to publishable results due to confidentiality issues.
- Elimination of interference in connection with cyclic on/off switching, for instance by implementing a proportional–integral–derivative-controlled thermostat (cf. Ref. [49]).
- Spreading multiple openings during an hour randomly over that hour. Some first trials where we implemented this indicated that the influence of the frequency of door openings is greater than that of their duration, and therefore, door openings—and mitigation thereof—may have more impact than the presented findings have suggested after all.
- Other characteristics that may be hidden in the TPUI, such as preferences for hours of the day or weekdays when opening the door, in combination with the statistical descriptors presented in Sec. 3.1, in order to construct more complex single-cycle patterns that provide better predictions of the influence of door openings. In addition, these features can possibly be used to (i) apply machine-learning to create fast-executing models that replace simulations for a given design variant, and (ii) cluster households and identify clusters of typical types of households. This will also require collecting data from more fielded units.

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. Some of our current findings may be specific for refrigeration appliances, such as those that can be attributed to interference due the compressor on/off cycle. It is possible that for other products cyclic use patterns representing user actions can be deployed to drastically reduce simulation time, or that more spectacular influences of usage can be uncovered and mitigated. Experience with more products may lead to a generalized approach for implementing and applying TPUI-based simulations.

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Nomenclature

d = relative influence of door openings on electricity consumption, %

[6]http://www.falcon-h2020.eu/

E = energy, kWh
$\bar{f}$ = daily average number (frequency) of door openings
t = time, s, h or days
Δt_{tot} = total time interval covered by the considered or simulated samplings belonging to one unit, s or days
$\overline{\Delta t_{\text{daily}}}$ = average door-open time per day, s
$\overline{\Delta t_{\text{i}}}$ = average time (duration) per door opening, s
$\overline{\Delta t_{ij}}$ = average time between two subsequent door openings, s or days

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