Assessing Human Activity in Elderly People's Homes Using the Dempster-Shafer Theory

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Keywords: Human Activity Recognition, Uncertainty Quantification, Ambient Assisted Living, Activities of Daily Living.

Abstract: The increasing elderly population living alone, alongside caregiver shortages, has accelerated research in Ambient Assisted Living (AAL). A recent trend employs smart meters and Non-Intrusive Load Monitoring (NILM) to assess daily activities by analyzing device-specific power usage. This work explores the use of Dempster-Shafer Theory (DST) to enhance NILM-based anomaly detection in daily routines. Evaluated on the SynD dataset, our approach identifies deviations such as unexpected appliance use and inactivity. Results demonstrate DST's potential for non-intrusive elderly monitoring, with future research focusing on real-world validation.

1 INTRODUCTION

By 2050, the population of people aged 65+ is projected to rise significantly (Eurostat, 2020). Over the last 20 years, the number of elderly living alone has increased by 19 %. In Germany, 96 % of those aged 65+ live in private homes, with only 4 % in nursing homes (Destatis, 2023). Many prefer independent living, yet loneliness and social isolation increase the risk of dementia (Lazzari and Rabottini, 2022). A survey across 10,000 individuals aged 80+ in Germany found that 18.1 % suffered from dementia and 24.9 % had mild cognitive problems (Brijoux and Zank, 2023). The ageing population and caregiver shortage, have led to extensive research in Ambient Assisted Living (AAL) (Alcala et al., 2017b).

AAL leverages technology and data collection to support elderly care. Monitoring methods are categorized into direct (wearable sensors) and indirect (environmental sensors). While direct methods provide precise physiological data (e.g. heart rate), they are intrusive and suited for high-risk patients (Alcala et al., 2017b). Indirect methods, such as motion sensors, are less accepted due to cost and perceived intrusiveness (Chalmers et al., 2016; Alcala et al., 2015).

Smart meters, increasingly deployed to modernize electricity networks (McLoughlin et al., 2015), record real-time energy consumption and transmit data for monitoring and billing (Zheng et al., 2013). Their widespread adoption presents a scalable alternative to traditional ambient sensors.

Non-Intrusive Load Monitoring (NILM) enables monitoring of Activities of Daily Living (ADLs) via household appliance usage (Bousbiat et al., 2022). Proposed by Katz, ADLs include essential tasks like eating and bathing (Katz et al., 1963). Deviations in energy data may indicate early cognitive decline (Bousbiat et al., 2022). The challenge lies in detecting such deviations reliably.

This paper provides the following contributions:

1. A framework for applying Dempster-Shafer Theory (DST) to detect human activity from smart meter data.
2. A method for inactivity pattern detection.
3. A classification method to identify anomalies in elderly daily activities.

2 RELATED WORK

Alcala et al. (2017a, 2015, 2017b) have significantly contributed to NILM-based human activity assessment. Their first approach (Alcala et al., 2015) utilizes a difference Hidden Markov Model (HMM) to detect appliance use from aggregated smart meter data and models appliance occurrences via a Poisson distribution with a log Gaussian Cox process. The

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Meyer, S. S., Wilhelm, S. and Wahl, F.
Assessing Human Activity in Elderly People's Homes Using the Dempster-Shafer Theory.
DOI: 10.5220/0013354100003938

In *Proceedings of the 11th International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2025)*, pages 291-301
ISBN: 978-989-758-743-6; ISSN: 2184-4984

method, evaluated on the HES dataset, enabled early intervention in 25 of 35 households and reduced false alarms. This study extends their work by incorporating multiple appliances.

Alcala et al. (2017a,b) also compared Gaussian Mixture Model (GMM) and DST for monitoring household activity. GMM trains probabilistic appliance models, computing a daily likelihood score, while DST generalizes Bayesian theory by defining belief and plausibility bounds to handle uncertainty in non-deterministic human behavior. Dempster's rule of combination aggregates belief assignments from different appliances, providing a normality score. DST outperformed GMM in detecting short- and long-term deviations (Alcala et al., 2017b). This study implements DST to simulate behavioral changes and emergencies.

Bousbiat et al. (2022) propose an interactive framework for activity monitoring based on user profiles, integrating load disaggregation, activity tracking, and feedback management. Activities are modeled via activity curves and self-similarity measures, stored in an observation database. Daily reports are compared using the Jensen-Shannon Divergence. While some anomalies were undetected, the framework showed overall acceptable performance, though it relied on single-appliance analysis.

Chalmers et al. (2019) explored NILM for ADLs assessment in dementia care. A six-month clinical trial tested Support Vector Machine and Random Decision Forest classifiers, achieving high sensitivity in detecting appliances. Behavioral patterns were modeled as feature vectors, analyzed through seven observation windows, Sankey diagrams, and Z-scores to detect anomalies. The approach successfully identified behavioral changes such as sundowning syndrome. Inspired by this, we evaluate DST for detecting similar conditions.

3 METHODOLOGY

Our approach extends Alcala et al. (2017b) by dividing the process into two phases: Observation and Evaluation. We first introduce DST.

3.1 Dempster-Shafer Theory (DST)

DST generalizes Bayesian probability theory and provides a framework for handling epistemic uncertainty (Sentz and Ferson, 2002). Instead of assigning precise probabilities, it maps probability mass to sets or intervals, interpreted as evidential weights (Rakowsky, 2007). DST consists of three components: *basic assignment*, *belief and plausibility*, and *Dempster's rule of combination*.

3.1.1 Basic Assignment

Basic assignment, denoted by m, maps the power set 2^Ω to the interval $[0,1]$:

$$m : 2^\Omega \rightarrow [0,1] \tag{1a}$$

$$m(\emptyset) = 0 \tag{1b}$$

$$\sum_{A \subseteq 2^\Omega} m(A) = 1 \tag{1c}$$

Unlike probability functions, m does not necessarily satisfy $m(\Omega) = 1$, nor does $m(A) \leq m(B)$ if $A \subset B$ (Rakowsky, 2007).

3.1.2 Belief and Plausibility

Belief $bel(A)$ sums basic assignments for subsets $B \subseteq A$, while plausibility $pl(A)$ sums assignments for sets where $B \cap A \neq \emptyset$:

$$bel(A) = \sum_{B \subseteq A; B \neq \emptyset} m(B) \tag{2a}$$

$$pl(A) = \sum_{B \cap A \neq \emptyset} m(B) \tag{2b}$$

$$bel(a) \leq m(A) \leq pl(a) \tag{2c}$$

The difference $pl(A) - bel(A)$ quantifies uncertainty (Klir and Wierman, 1999). Belief and plausibility should not be seen as complementary but rather as bounds on probability.

3.1.3 Dempster's Rule of Combination

Dempster's rule aggregates independent basic assignments m_1 and m_2:

$$m_{1,2}(\emptyset) = 0 \tag{3a}$$

$$m_{1,2}(A) = \frac{\sum_{B \cap C = A \neq \emptyset} m_1(B) m_2(C)}{1 - K} \tag{3b}$$

$$K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C) \tag{3c}$$

The denominator normalizes conflicting assignments (Shafer, 1986).

3.2 Applying DST to Asses Human Activity

3.2.1 Observation Phase

Household activities are recorded over four months using individual appliance power readings from the SynD dataset (Klemenjak et al., 2020) and a HMM to detect 'switch-on' events.

3.2.2 Recording Activities and Probability Assignment

Whenever a 'switch on' event is detected, the timestamp is recorded and assigned to one of four time bins (t_i) of six-hour intervals. This process is repeated for each date and all appliances under consideration.

After the observation phase, the data is stored in a Pandas data frame. The value at index (day, t_i) represents the frequency of appliance use for a given day and time frame. Probabilities $P(t_i)$ are then assigned by normalizing each row (n) by its total count (N):

$$P(day, t_i) = n_{day,t_i}/N_{day} \tag{4}$$

3.2.3 Evaluation Phase

After the observation phase and probability assignment, DST is applied to assess household activities. This involves computing basic assignments (Section 3.2.4), combining them across appliances and time frames (Section 3.2.5), and deriving *belief* and *plausibility* measures.

The frame of discernment (Ω) consists of two hypotheses: 'normal pattern' (h_1) and 'abnormal pattern' (h_2). The power set (2^Ω) also includes the combined hypothesis 'normal or abnormal pattern' (h_3) and the null set ($\emptyset$):

$$h_1 \text{ (normal pattern)}, \quad h_2 \text{ (abnormal pattern)} \tag{5a}$$

$$h_3 = h_1 \cup h_2 \quad \text{(normal or abnormal pattern)} \tag{5b}$$

$$\Omega = \{h_1, h_2\}, \quad 2^\Omega = \{\emptyset, h_1, h_2, h_3\} \tag{5c}$$

3.2.4 Basic Assignment and Weighing

Basic assignments are computed based on detected 'switch-on' events. When the HMM detects a transition from 'off' to 'on', the timestamp is stored in a Pandas data frame. For each time frame t_i, the recorded event count is used to weigh probabilities $P(day, t_i)$, as defined in Equations 6.

$$m_{date,t_i}(h_1) = \begin{cases} P(day, t_i) \times C_0, & \text{if event} \\ (1 - P(day, t_i)) \times C_1, & \text{if not event} \end{cases} \tag{6a}$$

$$m_{date,t_i}(h_2) = \begin{cases} (1 - P(day, t_i)) \times C_0, & \text{if event} \\ P(day, t_i) \times C_1, & \text{if not event} \end{cases}$$

$$\text{with } \Delta t_i \in [0, 24) \tag{6b}$$

$$m_{date,t_i}(h_3) = 1 - (m_{date,t_i}(h_1) + m_{date,t_i}(h_2)) \tag{6c}$$

The certainty constants C_0 and C_1 (ranging from 0 to 1) encode uncertainty and depend on appliance usage. In Alcala et al. (2017b), they were empirically set to $C_0 = 0.9$ and $C_1 = 0.1$, with a 6-hour evaluation window. This implies a 10 % uncertainty in event detection and 90 % in event absence.

Absence of an event does not necessarily indicate an abnormal pattern, as human behavior is unpredictable. DST manages uncertainty, unlike Bayesian approaches that rely solely on probabilities. Furthermore, event occurrence does not inherently imply normality but contributes additional information, reducing uncertainty by 10 % (Alcala et al., 2017b).

3.2.5 Combining Basic Assignments

After computing basic assignments (Section 3.2.4), Dempster's rule of combination aggregates them across appliances and time frames t_i. This ensures that evidence from multiple sources contributes to an overall activity assessment.

To illustrate the process, Table 1 presents arbitrary basic assignments for appliances X and Y.

Table 1: Basic assignments for appliances X and Y (Alcala et al., 2017b).

Appliance X	2^Ω	Appliance Y
$m_{date,t_i}(h_1) = 0.8$	h_1	$m_{date,t_i}(h_1) = 0.6$
$m_{date,t_i}(h_2) = 0.1$	h_2	$m_{date,t_i}(h_2) = 0.2$
$m_{date,t_i}(h_3) = 0.1$	$h_1 \cup h_2$	$m_{date,t_i}(h_3) = 0.2$

Each set of hypotheses is then combined by computing intersections, as shown in Table 2. The intersection of h_1 and h_2 is the empty set, as both patterns cannot coexist.

Table 2: Combining sets of hypotheses for appliances X and Y (Alcala et al., 2017b).

$\cap$	h_{1x}	h_{2x}	h_{3x}
h_{1y}	h_1	$\emptyset$	h_1
h_{2y}	$\emptyset$	h_2	h_2
h_{3y}	h_1	h_2	h_3

Table 3 represents the product of basic assignments for appliances X and Y.

Table 3: Products of basic assignments for appliances X and Y (Alcala et al., 2017b).

$\cdot$	$m(h_1)_x$	$m(h_2)_x$	$m(h_3)_x$
$m(h_1)_y$	$0.6 \cdot 0.8$	$0.6 \cdot 0.1$	$0.6 \cdot 0.1$
$m(h_2)_y$	$0.2 \cdot 0.8$	$0.2 \cdot 0.1$	$0.2 \cdot 0.1$
$m(h_3)_y$	$0.2 \cdot 0.8$	$0.2 \cdot 0.1$	$0.2 \cdot 0.1$

The combined basic assignments ($m(h_1)$, $m(h_2)$,

$m(h_3)$) are calculated using:

$$K = 0.8 \cdot 0.2 + 0.6 \cdot 0.1 \tag{7a}$$

$$m(h_1) = \frac{0.8 \cdot 0.6 + 0.1 \cdot 0.6 + 0.8 \cdot 0.2}{1-K} \tag{7b}$$

$$m(h_2) = \frac{0.1 \cdot 0.2 \cdot 3}{1-K} \tag{7c}$$

$$m(h_3) = \frac{0.1 \cdot 0.2}{1-K} \tag{7d}$$

Finally, *belief* and *plausibility* measures are computed as follows:

$$bel(h_1) = 0.89, \quad pl(h_1) = 0.92 \tag{8a}$$

$$bel(h_2) = 0.08, \quad pl(h_2) = 0.1 \tag{8b}$$

$$bel(h_3) = 1, \quad pl(h_3) = 1 \tag{8c}$$

Table 4 summarizes the results.

Table 4: Summary of results (Alcala et al., 2017b).

2^Ω	$m(t_i)$	$bel(t_i)$	$pl(t_i)$
h_1	0.89	0.89	0.92
h_2	0.08	0.08	0.1
h_3	0.02	1	1

The same process is repeated across time frames to accumulate a daily basic assignment.

4 EVALUATION

4.1 Overview

Figure 1 presents the workflow, from data ingestion and power processing to the identification of anomalies based on *belief* and *plausibility* thresholds.

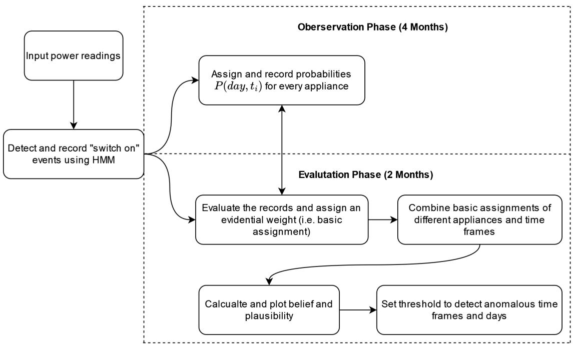


Figure 1: Workflow overview.

Selected appliances should be frequently used, manually operated, and associated with ADLs. We chose an electric kettle, coffee machine, microwave, television, hairdryer, toaster, and mini oven. Their high power consumption enhances detectability in NILM-based disaggregation. Unlike Alcala et al. (2017b), we excluded low-power appliances such as lamps.

4.2 Observation Phase Workflow

Power readings from the selected appliances were split into observation (4 months) and evaluation (2 months) data. 'Switch-on' events detected by the HMM were recorded for probability assignment 3.2.2. Figure 2 visualizes probability distributions for the coffee machine.

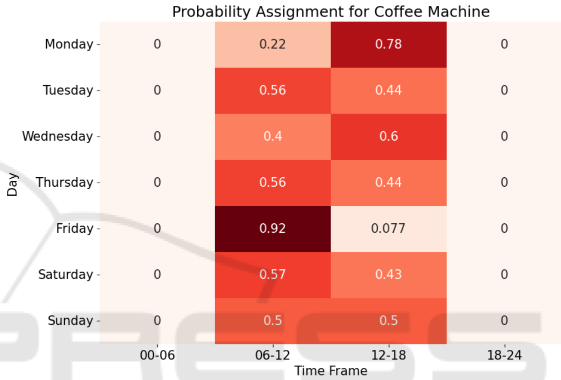


Figure 2: Probability assignment for coffee machine.

4.3 Evaluation Phase Workflow

The last two months of data were used for evaluation. Detected 'switch-on' events were mapped to probability assignments ($P(day, t_i)$), and basic assignments were accumulated across appliances and time frames to create a daily activity profile.

5 RESULTS

This Section discusses the results obtained using the workflow shown in Figure 1, focusing on the evaluation phase. It also covers how this DST configuration handles simulated emergencies and behavioural changes resulting from manipulating intermediate steps.

5.1 Plotting Belief and Plausibility

Once the evaluation phase begins and the basic assignments are mapped, the *belief* and *plausibility* measures are calculated and plotted on a line chart as

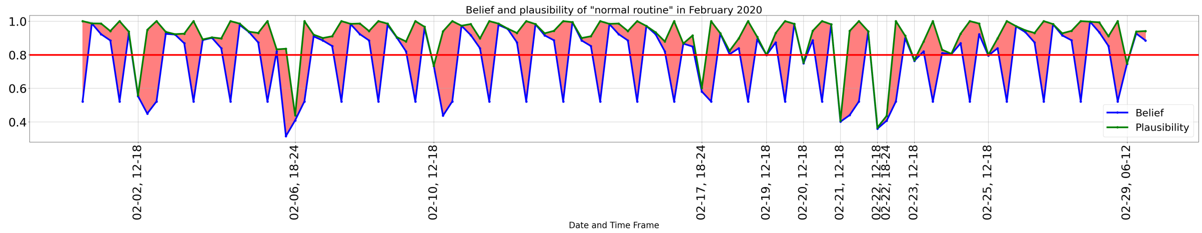


Figure 3: *Belief* and *plausibility* of h_1 in February 2020 (accumulated basic assignment of appliances).

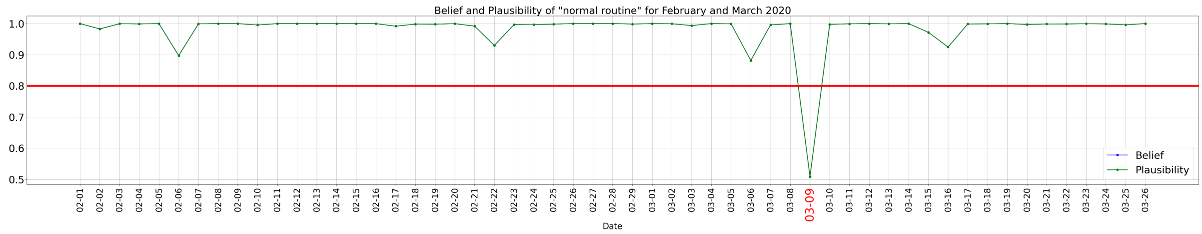


Figure 4: *Belief* and *plausibility* of h_1 (accumulated basic assignment of appliances and time frames).

suggested by Alcala et al. (2017b). Figures 3 and 7a display the *belief* and *plausibility* of the accumulated basic assignments of various appliances for February and March 2020, represented by the blue and green line respectively. The size of the red area between these lines indicates the level of uncertainty. Therefore, the larger the red area, the more uncertainty there is regarding h_1 ('normal pattern'). Accumulating for a daily basic assignment reduces the uncertainty, as shown in Figure 4. As it is done in the original study (Alcala et al., 2017b) a line at $y = 0.8$ represents the threshold. Therefore, if the value of *plausibility* and *belief* for a given time frame or day are below 0.8, it is considered 'anomalous'. Dates and time frames considered 'anomalous' are displayed on the x-axis.

5.2 Chart Analysis

Monday, March 9th, is the only day on the daily basic assignment chart in Figure 4 that is below the threshold. The appliances used on this day and the time frame in which they were used are shown in Table 5. Any differences between the expected and actual use of appliances in regards to the time frame, as well as the resulting increase in belief assignment for the corresponding hypothesis, are also shown in Table 5.

Unexpected appliance usage increases the belief assignment (m) in both the expected and actual usage time frames. Consequently, basic assignments $m(h_2)$ and $m(h_3)$ rise, as shown in columns 4 and 5 of Table 5. This indicates that unexpected usage raises $m(h_2)$, while absence increases $m(h_3)$.

6 SIMULATING ANOMALOUS BEHAVIOUR

The appliance usage data showed no signs of anomalous behaviour. Therefore, we tried to simulate anomalous behaviour, taking into consideration the baseline usage patterns of the appliances considered. This is done by changing intermediate steps. Because of how DST works, it's easy to simulate emergencies. All that needs to be done is to add events at odd times or remove events within a certain time frame. To add or remove an event, the number of detected 'switch-on' events in a given time frame can be either set to 0 or 1. From now on, February 15th will be used to test different situations. Appliances used on this day are shown in Figure 5, and the accumulated basic assignments of appliances are presented in Table 6a.

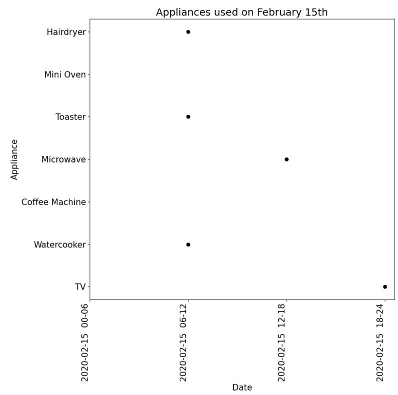


Figure 5: Appliances used on February 15th, 2020.

Table 5: Appliances used on March 9th and the subsequent increase basic assignment m.

Appliance	**Expected Use**	**Actual Use**	**Increase (Expected t_i)**	**Increase (Actual t_i)**
Coffee Machine	12-18	06-12	h_3	h_2
Toaster	06-12	-	-	h_3
Electric Oven	06-12	12-18	h_3	h_2
Television	18-24	12-18	h_3	h_2

Table 6: Comparison of basic assignments on February 15th.

(a) Basic assignments on February 15th (not manipulated).

t_i	$m(h_1)$	$m(h_2)$	$m(h_3)$
00-06	0.5217	0.0	0.4783
06-12	0.9822	0.0164	0.0014
12-18	0.9222	0.0143	0.0635
18-24	0.8849	0.0592	0.0559
15.02	0.99	0.0	0.0

(b) Basic assignments on February 15th (midday inactivity).

t_i	$m(h_1)$	$m(h_2)$	$m(h_3)$
00-06	0.5217	0.0	0.4783
06-12	0.9822	0.0164	0.0014
12-18	0.2884	0.1888	0.5228
18-24	0.8849	0.0592	0.0559
15.02	0.99	0.0	0.0

(c) Basic assignments on February 15th (half day inactivity).

t_i	$m(h_1)$	$m(h_2)$	$m(h_3)$
00-06	0.5217	0.0	0.4783
06-12	0.9822	0.0164	0.0014
12-18	0.2884	0.1888	0.5228
18-24	0.4522	0.0489	0.4989
15.02	0.996	0.0041	0.0002

(d) Basic assignments on February 15th (unusual activity).

t_i	$m(h_1)$	$m(h_2)$	$m(h_3)$
00-06	0.0810	0.8271	0.0919
06-12	0.9822	0.0164	0.0014
12-18	0.9222	0.0143	0.0635
18-24	0.8849	0.0592	0.0559
15.02	0.99	0.0	0.0

6.1 Midday Inactivity

To simulate midday inactivity, microwave use is removed in the 12-18 time frame. This change increases the uncertainty for this period. Consequently, the basic assignment $m(h_3)$ increases and $m(h_1)$ decreases as shown in Tables 6a and 6b.

6.2 Half-Day Inactivity

Half-day inactivity builds on midday inactivity by removing television use after 18:00hrs. As with the removal of microwave use in midday inactivity, the removal of television use also increases uncertainty in the 18-24 time frame as shown in Tables 6a and 6c.

6.3 Activity at an Unusual Time

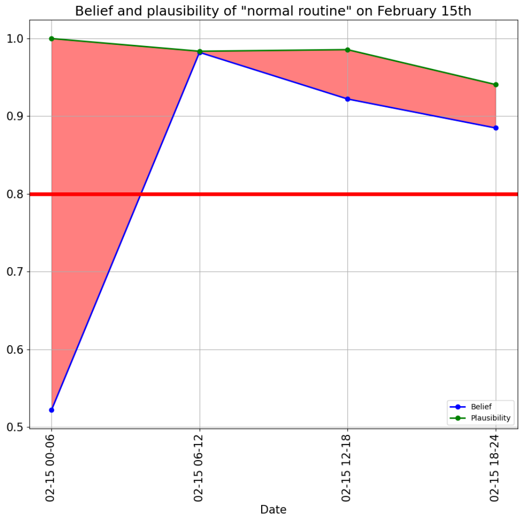
Adding events to unusual time frames is a method of simulating abnormal activity. Between the hours of 00-06 and 18-24, there is typically less activity than during the other hours. Therefore, the use of a coffee machine during the time frame 00-06 has been added. Compared to the half-day and midday inactivity, this leads to a decrease in uncertainty and increases the basic assignment $m(h_2)$ instead of $m(h_3)$ as shown in Table 6d. As it was the case for the previous simulations, there is no effect on the daily basic assignment.

7 SIMULATING BEHAVIOURAL CHANGES

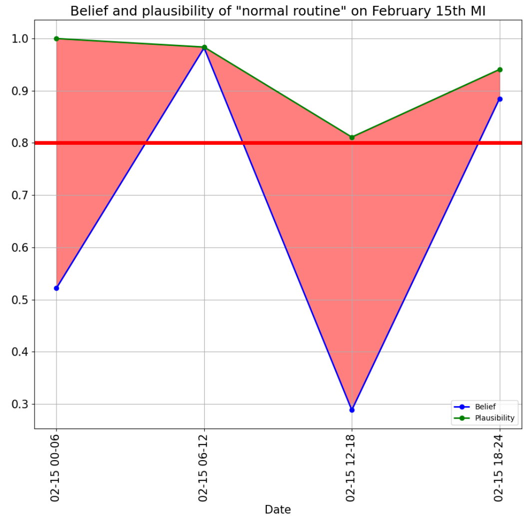
Deviations from regular daily routines, accompanied by changes in behaviour, may indicate the presence of dementia. These abnormalities tend to become more frequent and severe as dementia progresses (Chalmers et al., 2019). In this section, the results of simulating sundowning syndrome and mild cognitive impairment, which is a precursor to dementia, are presented.

7.1 Sundowning Syndrome

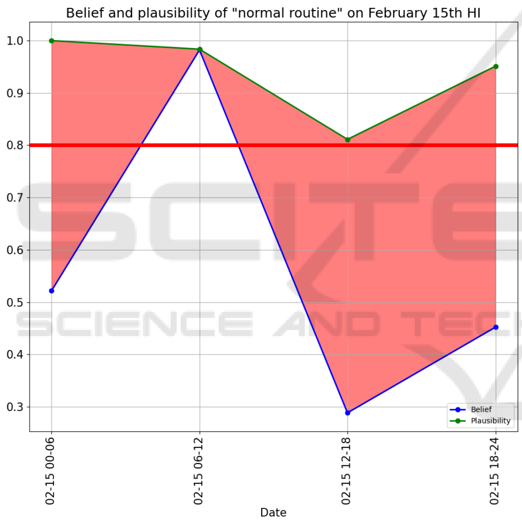
One well-known condition in dementia patients is the sundowning syndrome, where a person may exhibit certain behaviours in the latter half of the day. Monitoring power consumption over time can help identify these behavioural changes (Chalmers et al., 2019).



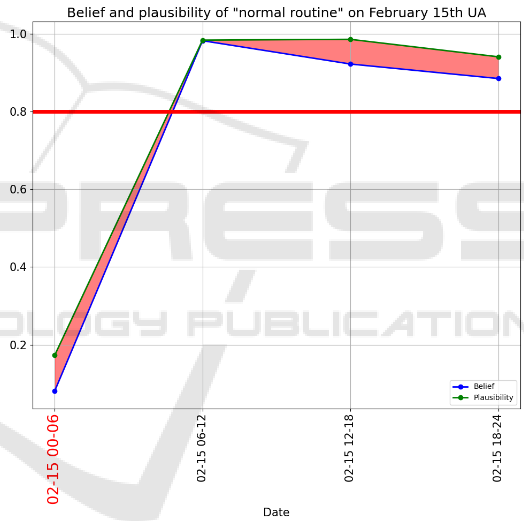
(a) *Belief* and *plausibility* on February 15th (not manipulated).



(b) *Belief* and *plausibility* on February 15th (midday inactivity).



(c) *Belief* and *plausibility* on February 15th (half day inactivity).



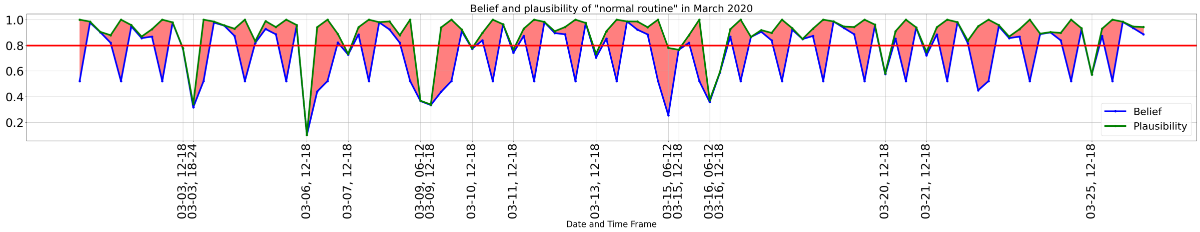
(d) *Belief* and *plausibility* on February 15th (unusual activity).

Figure 6: Comparison of *belief* and *plausibility* on February 15th.

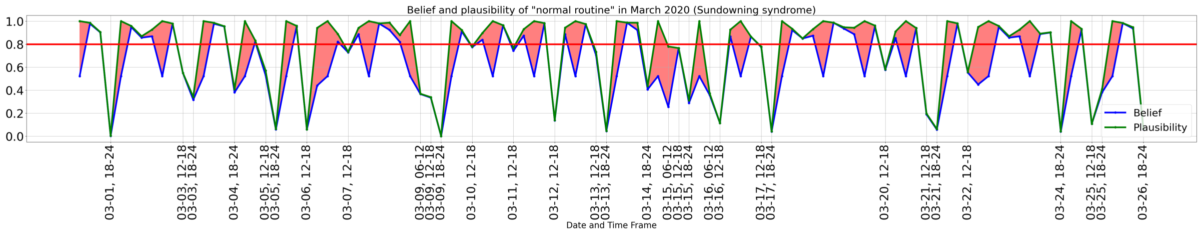
To simulate this, random events were added in the March 12-18 and 18-24 time frames, including random use of the kettle, coffee machine and toaster. Figures 7b and 8a illustrate the effect of these randomly added events. Compared to the original results, where only 16 time frames were considered anomalous, 32 time frames are now considered abnormal. Similarly, the impact is evident in the daily accumulated basic assignments chart, which now shows 8 abnormal days compared to only one previously. In total, all 16 time frames that were previously considered normal now have time frames with at least one random event added to them.

7.2 Mild Cognitive Impairment

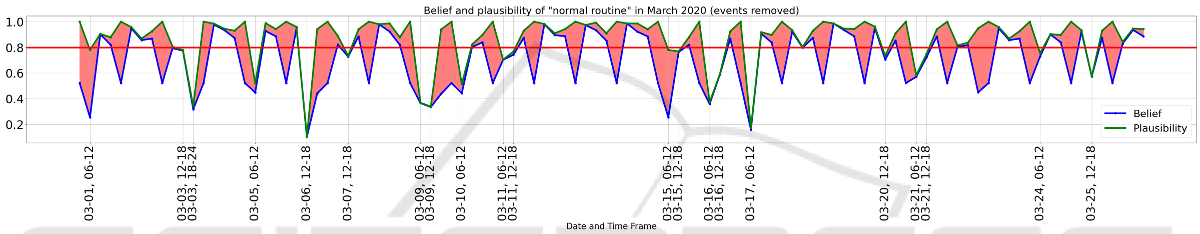
Memory is one of the first skills of daily living to be impaired in people with mild cognitive impairment (Scheerbaum et al., 2023). To simulate this, the events of the same appliances were randomly removed from the time frames 06-12 and 12-18. (see Figures 7c and 8b) As evident in Figure 7c, there are visibly more time frames now considered anomalous. Prior to the events being removed, 16 time frames were considered anmoulous. Now the number of time frames considerd anmoulous is 21. Only in about half of the cases where events were removed from certain



(a) *Belief* and *plausibility* of h_1 in March 2020.

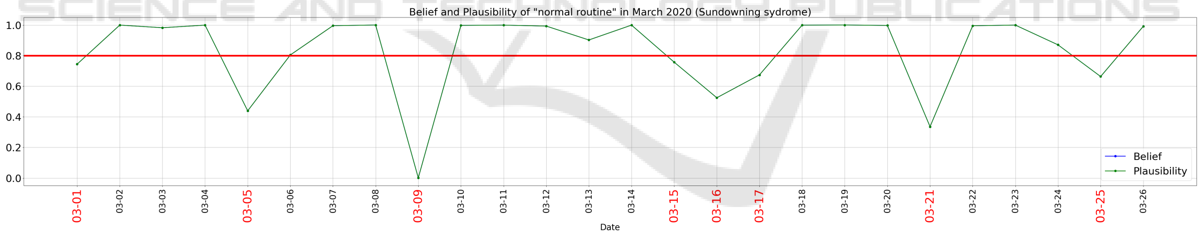


(b) *Belief* and *plausibility* of h_1 in March 2020 (Sundowning syndrome).

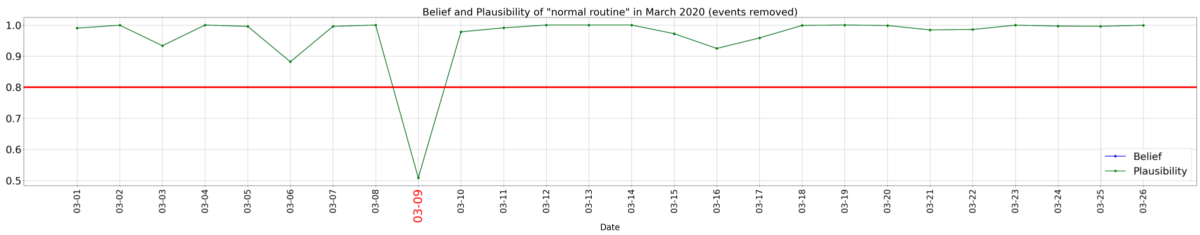


(c) *Belief* and *plausibility* of h_1 in March 2020 (Mild cognitive impairment).

Figure 7: Effect of randomly removed events.



(a) *Belief* and *plausibility* of h_1 March 2020 (Sundowning syndrome).



(b) *Belief* and *plausibility* of h_1 March 2020 (Mild cognitive impairment).

Figure 8: Effect of randomly added events.

time frames did this affect their 'normality'. These figures should not be interpreted as a measure of accuracy. Figure 8b, which is the plot for the daily basic assignments for March 2020, still shows the 9th March 2020 as the only anomalous day.

Table 7: Appliance used on March 9th and the subsequent increase in basic assignment (reconfigured).

Appliance	**Expected Use**	**Actual Use**	**Increase (Expected t_i)**	**Increase (Expected t_i)**
Coffee Machine	12-18	06-12	h_2	h_3
Toaster	06-12	-	-	h_2
Electric Oven	06-12	12-18	h_2	h_3
Television	18-24	12-18	h_2	h_3

8 DISCUSSION

8.1 Analyzing Dempster's Rule of Combination

Analyzing the results in Section 5 reveals key observations. Unexpected appliance use increases $m(h_2)$ in the actual usage time frame and $m(h_3)$ in the expected one. Conversely, if an appliance is not used when expected, $m(h_3)$ increases in the respective time frame. Unusual appliance usage significantly impacts the accumulated daily basic assignment, affecting *belief* and *plausibility*, while inactivity has little effect.

These effects arise because Dempster's rule disregards h_3 when combining hypotheses, as shown in Equations 9.

$$h_1 \cap h_3 = h_1 \tag{9a}$$

$$h_2 \cap h_3 = h_2 \tag{9b}$$

As a result, missing events do not affect daily basic assignments. This explains why a single omitted event had little impact, as seen in Section 7.2.

8.2 Evaluating the Basic Assignment Configuration

As shown in Equations 10, a high evidential weight is assigned to h_3 even when the probability of use is low. This results from the certainty constants ($C_0 = 0.9$, $C_1 = 0.1$), which attribute high uncertainty to inactivity. The original study (Alcala et al., 2017b) included appliances like lamps and printers, which are rarely used or have low power consumption. Assigning high uncertainty ensures these cases are disregarded (Section 8.1).

Inactivity

High Probability

$$P(t_i) = 0.8 \tag{10a}$$

$$m(h_1) = (1-0.8)\times 0.1 = 0.02 \tag{10b}$$

$$m(h_2) = 0.8\times 0.1 = 0.08 \tag{10c}$$

$$m(h_3) = 1-(0.02+0.08) = \mathbf{0.9} \tag{10d}$$

Low Probability

$$P(t_i) = 0.2 \tag{10e}$$

$$m(h_1) = (1-0.2)\times 0.1 = 0.08 \tag{10f}$$

$$m(h_2) = 0.2\times 0.1 = 0.02 \tag{10g}$$

$$m(h_3) = 1-(0.02+0.08) = \mathbf{0.9} \tag{10h}$$

Activity

Low Probability

$$P(t_i) = 0.2 \tag{10i}$$

$$m(h_1) = 0.2\times 0.9 = 0.18 \tag{10j}$$

$$m(h_2) = (1-0.2)\times 0.9 = \mathbf{0.71} \tag{10k}$$

$$m(h_3) = 1-(0.18+0.71) = 0.11 \tag{10l}$$

8.3 Re-Configuring the Basic Assignment Process

The basic assignment process is subjective, allowing it to be reconfigured. Unlike the basic assignment configuration used by the authors in (Alcala et al., 2017b), where h_3 is assigned a high evidential weight on inactivity. In the case of inactivity, this configuration assigns h_2 a high evidential weight. The certainty constants C_0 and C_1 can be reconfigured to enable this. To do this, C_1 can be set to a higher value, e.g. 0.5, which in turn only assigns a 50 % uncertainty when an appliance is not used. What makes this feasible is the choice of appliances used for this evaluation, as they are more critical to the daily routine compared to those used for the evaluation in (Alcala et al., 2017b). Equations 11 show the results of this configuration. While this configuration initially appears superior, it presents several issues. First, it does not account for routine variations. Human behavior is unpredictable, and earlier or later appliance usage does not necessarily indicate an abnormal pattern. As a result, March 9th is still classified as anomalous despite only minor deviations in usage times.

Additionally, assigning a high evidential weight to h_2 during inactivity introduces distortions. If an appliance is used earlier or later than usual, $m(h_2)$ unnecessarily increases in the expected time frame. In periods of low activity, the absence of expected events inflates $m(h_1)$, overshadowing deviations such as missed TV usage in the 18-24 time frame.

Inactivity

High Probability

$$P(t_i) = 0.8 \tag{11a}$$
$$m(h_1) = (1-0.8) \times 0.7 = 0.14 \tag{11b}$$
$$m(h_2) = 0.8 \times 0.7 = \mathbf{0.56} \tag{11c}$$
$$m(h_3) = 1-(0.14+0.56) = 0.3 \tag{11d}$$

Low Probability

$$P(t_i) = 0.2 \tag{11e}$$
$$m(h_1) = (1-0.2) \times 0.7 = \mathbf{0.56} \tag{11f}$$
$$m(h_2) = 0.2 \times 0.7 = 0.14 \tag{11g}$$
$$m(h_3) = 1-(0.14+0.56) = 0.3 \tag{11h}$$

Activity

Low Probability

$$P(t_i) = 0.2 \tag{11i}$$
$$m(h_1) = 0.2 \times 0.9 = 0.18 \tag{11j}$$
$$m(h_2) = (1-0.2) \times 0.9 = \mathbf{0.71} \tag{11k}$$
$$m(h_3) = 1-(0.18+0.71) = 0.11 \tag{11l}$$

Table 7 illustrates these changes for March 9th. Despite reconfiguration, the day is still not identified as anomalous, except for deviations in the 18-24 time frame, which this approach does not adequately address.

8.4 Subjectivity of Anomalies

Defining abnormal activity patterns in the context of ADL can be challenging due to the non-deterministic and changeable nature of human behaviour. Therefore, it is important to distinguish between variation and deviation. Variations may refer to new habits and routines adopted by the person. Conversely, deviations, are categorical changes in routine that result in potentially abnormal patterns (Bousbiat et al., 2022). Bousbiat et al. (2022) 'This can be illustrated by the following scenario. A change in breakfast time for several consecutive days is considered a variation. However, the sudden cancellation of breakfast is considered a deviation. In summary, both variation and deviation can be associated with some kind of physical or cognitive impairment. Therefore, in both cases, a personal assessment by a professional is necessary.'

9 CONCLUSION AND FUTURE WORK

Our approach demonstrates potential for assessing human activity in the elderly. Simulating emergencies and behavioral changes, such as sundowning syndrome, yielded promising results. Event additions were reflected in both time-based and daily activity charts. However, our method struggles with event omissions, such as simulating mild cognitive impairment. The increased evidential weight for $m(h_3)$ in missing events is disregarded during basic assignment accumulation as explaned in Section 8.1. Consequently, unless all activity ceases, single-event omissions do not affect the aggregated basic assignment.

For low-performing NILM algorithms, this robustness prevents missed detections from distorting results. However, in high-accuracy NILM, unnoticed inactivity could be problematic. Detecting missed events is crucial for elderly activity assessment, necessitating validation on datasets from individuals with cognitive or physical impairments.

Identifying anomalies, especially inactivity, remains challenging. Plotting *belief* and *plausibility* of h_1 may not be optimal for practical applications. An automated classification method (Figure 9) could improve anomaly detection. The empirically set thresholds may require statistical optimization for robustness.

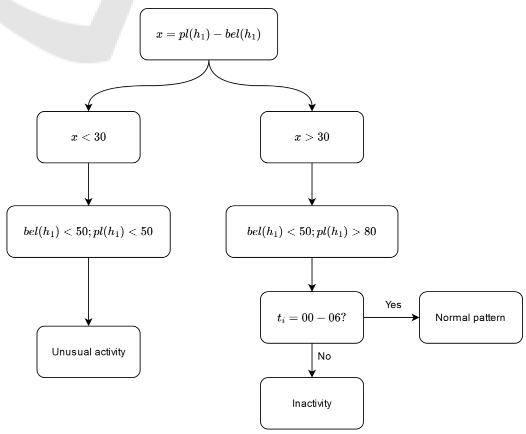


Figure 9: Proposal for automated activity classification.

Future research should explore anomaly classification by tracking appliance-specific basic assignments. Variations in h_1 may provide insights into the nature of deviations.

ACKNOWLEDGEMENTS

This research was funded by the Hightech Agenda Bavaria.

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