Water Detection and Monitoring Service for Energy-Efficient Home Automation

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研究動機

近年來水資源匱乏，節省用水是每個人都需要做的事。
但是目前多數的家庭僅能從兩個月一次的水費帳單中得知自己的總用水量，並無法分析自己在哪些方面用水較多。儘管可以使用多個智慧水表去統計住家的用水行為，但是因為建設與維護的成本過高，並不普及；
並且，漏水問題也是水資源浪費的一大原因。但是目前的**漏水偵測服務**太過單純，無法有效吸引更多用戶使用，需要有更多的誘因去吸引更多的使用者加入。

為了吸引更多人一起為省水盡一份心力，
因此設計出幾個目標：

減少建置成本：僅使用**單一智慧水表**（總用水量）去分析用戶的用水行為。
減少維護成本：分析「資料密度」對準確度的影響，以**減少水表資料回傳頻率**，節省用電。
增加建設誘因：透過此架構**建立智能家庭服務**，以吸引更多用戶使用此系統來協助省水。

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ABSTRACT

0.1 / Abstract

Abstract — Energy efficiency and home automation are becoming increasingly important. In this study, we design an energy-efficient home automation framework based on smart water meters (SWM) to save energy and improve quality of life. Through the proposed approach, various services including stay-up alarm, post-laundry weather forecast, insufficient water intake alarm, daily water behavior report, and water leak alert can be provided. More specific, we will use a single SWM to detect household water usage behavior and water leaks. Nonetheless, to prevent unnecessary electronic usage for SWMs, we also explored the relationship between effectiveness and different temporal densities. Therefore, SWMs do not have to collect and send usage information every second, but still have similar accuracy and precision.

示意圖(擷取自網路)：[Fluid Smart Water Meter | Uncrate]

Index Terms: Smart Water Meter, Home Automation, Water Leakage Detection, Water Behavior Detection

01
INTRODUCTION

1.1 / Smart Meter

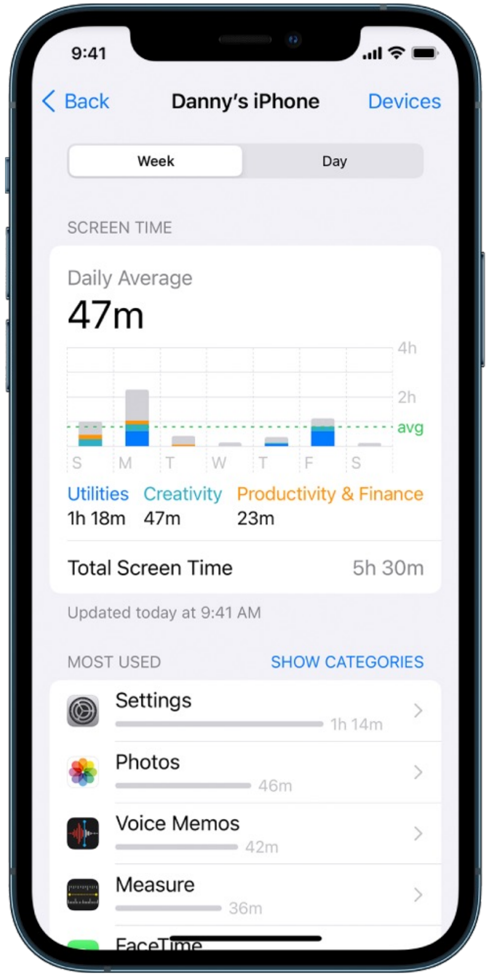
I. INTRODUCTION

Since the invention of the home smart meter, energy usage analysis has been considered not only in the factory but also in the home. Therefore, many studies based on smart meters have been proposed. Some researches use electricity smart meters (ESM) to reveal household characteristics [1, 2]. Some researches have explored the relation between ESM and integrated energy system [3]. Some researches aim to protect user privacy. Notable examples include [4, 5]. Some researchers provide a complete view, including anomaly detection, load forecasting, consumer segmentation, and demand response [6].

Not only electricity, but smart water meter (SWM)-based research is also increasing notably. Some researches build water management system with SWM [7]. Some researches provide a solution for connecting SWM to Internet of things (IoT) environment. Notable examples include [8, 9]. Some focus on reducing the electricity usage of a SWM [10, 11]. Some focus on detecting water leakage [12].

1.2 / Usage Reports

In this work, we will only focus on water domain.
With growing concerns about energy shortages, energy efficiency has become increasingly important in recent years. Everyone is be responsible for conserving water. However, most of us don't notice how many water conservation we do everyday. Similar problems have been found in smartphones. If we want to spend less time on our smartphones but we don't know which apps take the most times, we can simply see how much time we spend on each app by checking the weekly screen time report. Therefore, it would be useful for us to reduce our water usage if we had daily and weekly water usage reports like our smartphone's weekly screen time reports. To achieve this, we need to analysis data from SWMs. The best way to analysis household water consumption is to install multiple SWMs on different devices. We can then get usage information for every machine in the home and provide an accurate daily report of water usage. However, those who are struggling or living in older homes may be reluctant to incur the cost of installation and maintenance. Therefore, we explored the possibility of building energy-efficient homes using a single SWM for those who only have a smart meter for total water consumption. In addition, since water leakage problems can affect the accuracy of water behavior detection and wastewater, we combine the water leakage detection model with the daily water consumption report in the proposed system.



示意圖(擷取自網路)：[Fluid Smart Water Meter | Uncrate]

1.3 / Temporal Densities & Home Automata

As data is sent more frequently, smart meters will require more power. To reduce the electricity consumption of SWM, we also explored the relationship between effectiveness and different temporal densities for both water behavior detection and water leakage detection.
Furthermore, since we can detect water use behaviors, we can also provide home automation services. Overall, we will combine water behavior detection, water leakage detection, and home automation services in our work.

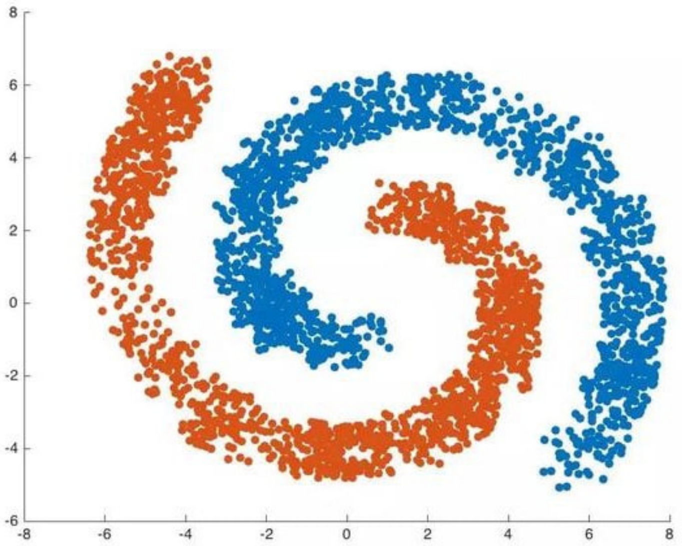
02

RELATED WORKS

2.1 / Leakage Detection

II. RELATED WORKS

In the water leakage detection experiment, we adopt the water leakage detection algorithm proposed by Lo-Paug-Yun Ting as our water leakage detection model. The algorithm is based on Density Applied Spatial Clustering with Noise (DBSCAN) combined with some rule-based models. However, the framework is based on a fixed temporal density, so we will retrain the model with different sample and label intervals to explore the relationship between effectiveness and different temporal densities.



DBSCAN(擷取自網路)：DBSCAN - Jason Chen's Blog (weebly.com)

03

Water Detection and Monitoring Service for Energy-Efficient Home Automation

3.1 / Sections

In this section, we divide the problem into five parts:

- **water behavior detection**
- **water leakage detection**
- **combination of water behavior and leakage detection**
- **home automation**
- **the whole system we proposed.**

3.2 / Water Behavior Detection

A. Water Behavior Detection

We use supervised model such as Support Vector Machine (SVM) as our water behavior detection model. The reason why we do not use deep models can be attributed to two factors: First, the accuracy of SVMs in our experiments is high enough to not require the use of more complex models. Second, the system cost of applying deep model to thousands of households is much higher than that of traditional machine learning models. SWM will collect total water consumption every sample interval. That is, if we have a sample interval of 3 minutes, we will have one cumulative water consumption record every 3 minutes. Detect interval means how often we detect behaviors. Therefore, if we have a sample interval of 1 minute and a detect interval of 15 minutes, system will detect behaviors every 15 minutes with 15 water consumption values.

Minimum, maximum, mean, skewness, and kurtosis will be adopted on total water consumption values and be used as our input features, and 5-fold cross validation and GridSearchCV were used.

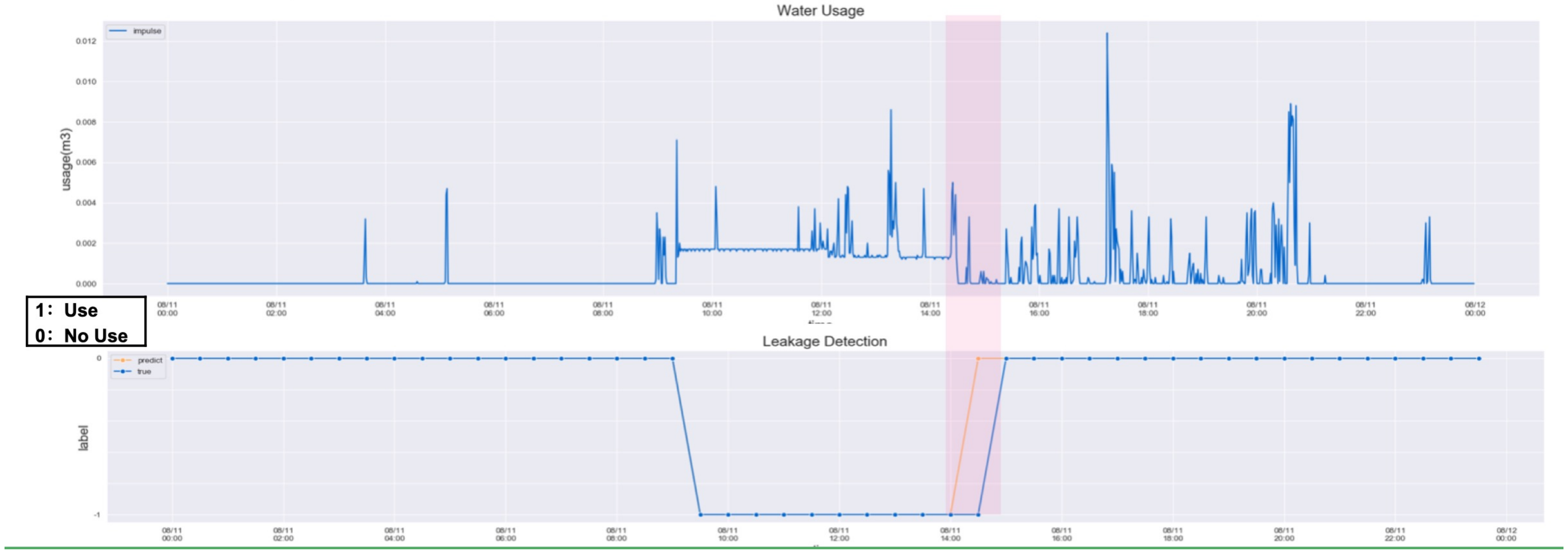
During the training phase, we try multiple behavioral labels, but only those with higher precision and accuracy are used as part of the daily or weekly report.

3.3 / Water Leakage Detection

B. Water Leakage Detection

We use DBSCAN mentioned in Sec. II-A as our water leakage detection model. In water leak detection results, precision ($TP / (TP + FP)$) and accuracy $(TP + TN / TP + TN + FP + FN)$ should be carefully considered.

- **Accuracy: 97.92% , Precision: 90.91%**



3.4 / Behavior X Leakage

C. Combination of Water Behavior Detection and Leakage Detection

Since the water behavior detection will be affected by the water leakage event, we designed the following rules: once the water leakage alarm occurs, the system will send the alarm information to the user through the communication software and mark the behavior detection in this time period as unreliable. As a result, we can provide more reliable water behavior detection reports without the uncertainty of water leakage events

3.5 / Home Automation

D. Home Automation

Since we can detect the behavior of water, we can provide the following services:

1) stay-up alarm

Since we can detect when the user is brushing their teeth each day, we can issue a stay-up alert. If the user brushes their teeth after 00:00 AM, the system sends a silent notification to the user's phone that it is time to go to bed.

2) post-laundry weather forecast

Since we can detect when the user is using the washing machine, we can publish useful post-laundry weather forecasts. Once the system detects that the user is using the washing machine, it sends weather forecast information for the next 12 hours to help the user decide whether to hang out the clothes or use the dryer.

3.5 / Home Automation

3) insufficient water intake alarm

Since we can detect and record the number of times a user urinates per day, we can alert at the end of the day if the number of urinations in a day is less than 70% of the historical record.

4) Energy-saving home automation

As we mentioned in Sec. I, if we provide daily and weekly water usage report to users, they might aware the water usage and reduce the unnecessary water behaviors. Also, several interest home automation which we mentioned above can be provide.

More specific, we will collect data with SWM and send it to local or remote server to detect behaviors. Once the events occur, server will send notification to user's phone, iPad, and smart TV if they have. Events include stay-up alarm, post-laundry weather forecast, insufficient water intake alarm, daily and weekly water behavior reports, and so on.

System structure is in Fig. 1.

3.6 / System Structure

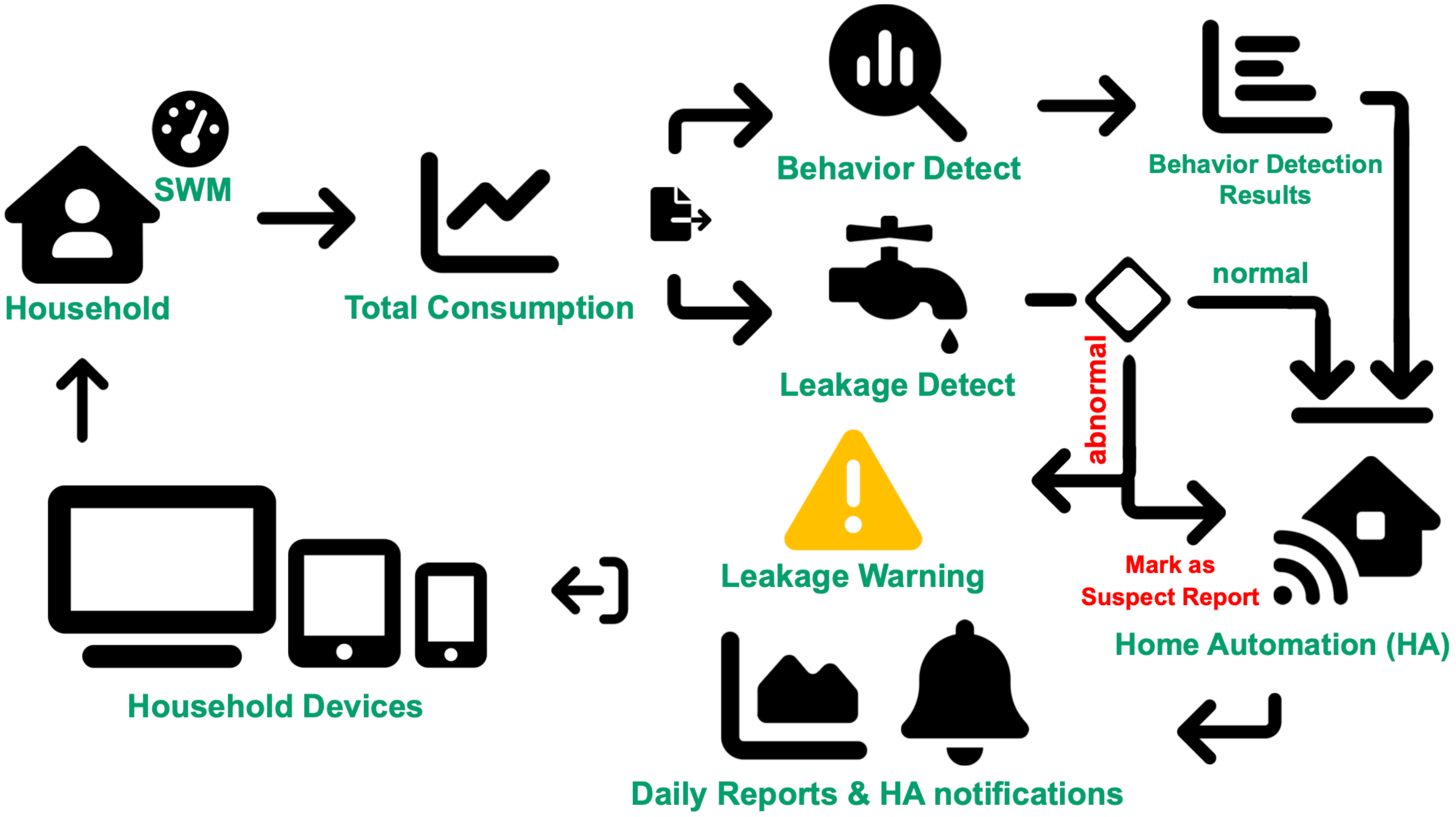


Fig. 1. System strcture

04

Experiments

4.1 / Model Architecture

IV. EXPERIMENTS

A. Model architecture

We used a variety of traditional machine learning methods to evaluate the effectiveness, including K-Neighbors Classifier (KNC), Support Vector Classifier (SVC), Decision Tree Classifier (DTC), Random Forest Classifier (RFC), AdaBoost Classifier (ABC), Gradient Boosting Classifier (GBC), Gaussian Naive Bayes (GNB), and Linear Discriminant Analysis (LDA). The KNC uses 5 neighbors and uniform weight. The SVC uses rbf kernel and scale gamma. The DTC uses Gini impurity with a minimum number of splits of 2. The RFC uses 100 trees in the forest and Gini impurity is used for the criterion function. The ABC uses estimators with a maximum of 50, and the learning rate is set to 1.0. The GBC uses deviance loss and 100 estimators. The GNB uses 1e-9 as maximum smoothing variance. The LDA uses singular value decomposition as it's solver.

For the water leak detection model, we combine the DBSCAN model with a rule-based model. The rule-based model is used to detect successive small and strong leaks.

4.2 / Datasets

B. Datasets

In experiments, we used four different datasets to evaluate the proposed framework.

a). Azbil-5day dataset: This dataset was collected by Azbil Corp., Japan. It contains a household's five-day total water consumption value and three water-use behavior labels. Behavioral labels included use of the toilet (denoted as toilet), use of the kitchen (denoted as kitchen), and use of the washing basin (denoted as W-Basin). The total water consumption value is accurate to 1 second/1 record, and the behavioral labels are accurate to 15 minutes/1 record.

b). Azbil-7day dataset: This dataset was collected by Azbil Corp., Japan. It contains a household's seven-day total water consumption value and nine water use behavior labels. Behavioral labels included brushing teeth (denoted as Teeth), washing face (denoted as Face), washing hand (denoted as Hand), urination (denoted as Urinate), defecation (denoted as Defecate), taking shower (denoted as Shower), use of washing machine (denoted as W-machine), and use of washing basin (denoted as W-basin). The total water consumption value is accurate to 1 minute/1 record, and the behavioral labels are accurate to 30 minutes/1 record.

azbil Azbil Corporation

4.2 / Datasets

c). Shalun-Dorm: This dataset was collected by NetDB Laboratory, NCKU, Taiwan. It contains four households' fourteen-day total water consumption value and leakage labels. Both of the total water consumption value and leakage labels are accurate to 1 minute/1 record.

d). Tokyo-A: This dataset was collected by Azbil Corp., Japan. First part of the dataset (denoted as Tokyo (August)) contains six household's one-day total water consumption value and leakage labels and one household's two-day total water consumption value and leakage labels. The second part of the dataset (denoted as Tokyo (October)) contains five household's one-day total water consumption value and leakage labels. Both of the total water consumption value and leakage labels in Tokyo (August) and Tokyo (October) are accurate to 1 minute/1 record.

4.3 / Water Behaviors Detection

B. Water Behaviors Detection

In this section, we focus on water behavior detection. As we mentioned in Sec. III, we have to explore two elements. First, the effectiveness of detecting water behaviors with a single SWM values. Second, the effectiveness on different temporal densities. We used eight different models and two different datasets Azbil-5day and Azbil-7day in our experiments. The detection interval value was fixed, and multiple sample intervals were tested. Minimum, maximum, mean, skewness, and kurtosis were used as our input features, and 5-fold cross-validation was applied during training phase. Brief results for Azbil-5day and Azbil-7day dataset are shown in Tab. I and Tab. II. The full version of the results can be found in Tab. V and Tab. VI.

4.3 / Water Behaviors Detection

TABLE I
BRIEF OF WATER BEHAVIOR ON AZBIL-5DAY DATASET. (15 MIN/1 DETECT)

FULL RESULTS CAN BE FOUND IN TABLE. V

	Toilet		Kitchen		W-Basin	
	Prec	Accu	Prec	Accu	Prec	Accu
SVC_{1s}	1.00	0.69	0.64	0.75	0.77	0.74
SVC_{15s}	1.00	0.69	0.64	0.75	0.77	0.74
SVC_{30s}	1.00	0.69	0.61	0.74	0.77	0.74
SVC_{1m}	0.96	0.67	0.61	0.74	0.77	0.74
SVC_{3m}	0.96	0.69	0.61	0.74	0.77	0.74
SVC_{5m}	1.00	0.70	0.61	0.74	0.77	0.74
Positive	47		25		32	
Total	78		78		78	

4.3 / Water Behaviors Detection

TABLE II

WATER BEHAVIOR DETECTION ON AZBIL-7DAY DATASET. (30 MIN/1 DETECT)

	Teeth		Face		Hand		Urinate		Defecate		Shower		Dishes		W-machine		W-Basin	
	P	A	P	A	P	A	P	A	P	A	P	A	P	A	P	A	P	A
SVC_{1m}	1.00	0.99	1.00	0.99	0.18	0.94	0.17	0.95	0.00	0.97	1.00	0.99	1.00	0.98	0.00	0.99	1.00	0.99
SVC_{3m}	1.00	0.99	1.00	0.99	0.06	0.92	1.00	0.95	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00	0.99
SVC_{5m}	1.00	0.99	1.00	0.99	1.00	0.97	1.00	0.95	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00	0.99
SVC_{10m}	1.00	0.99	1.00	0.99	1.00	0.97	1.00	0.95	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00	0.99
SVC_{15m}	1.00	0.99	1.00	0.99	1.00	0.97	1.00	0.95	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00	0.99
Positive	6		6		16		26		10		7		8		4		2	
Total	614		614		614		614		614		614		614		614		614	

4.4 / Water Behaviors Detection

According to the results, we found that for SVC models we can get similar precision and accuracy in Arbil-5days and Arbil-7days datasets for all sample interval. However, Precision and accuracy of Kitchen in Arbil-5days were slightly decreased as sample interval larger than 15 seconds. For water behaviors include washing face, washing hand, urination, defecation, and washing machine in Arbil- 7dats dataset with SVC models have higher precision with sampling interval value of 5, 10, 15 minutes instead of 1 minute. Overall, results were similar across all models for all intervals in the Arbil-5days dataset, but some models were less accurate for some of the models with too small or too large intervals in the Arbil-7days dataset. Note that the detection interval for the Arbil-5days dataset is 15 minutes, while the detection interval for the Arbil-7days dataset is 30 minutes.

4.5 / supplement

TABLE V

WATER BEHAVIOR ON AZBIL-5DAY DATASET. (15 MIN/1 DETECT) (FULL VERSION)

	Toilet		Kitchen		W-Basin	
	Prec	Accu	Prec	Accu	Prec	Accu
KNC$_{1s}$	0.91	0.76	0.56	0.71	0.74	0.78
SVC$_{1s}$	1.00	0.69	0.64	0.75	0.77	0.74
DTC$_{1s}$	0.91	0.75	0.75	0.83	0.75	0.76
RFC$_{1s}$	0.92	0.78	0.71	0.80	0.71	0.74
ABC$_{1s}$	0.92	0.78	0.73	0.80	0.68	0.73
GBC$_{1s}$	0.91	0.76	0.74	0.82	0.78	0.78
GNB$_{1s}$	0.87	0.61	0.64	0.76	0.73	0.74
LDA$_{1s}$	0.86	0.66	0.65	0.76	0.71	0.71
KNC$_{15s}$	0.94	0.78	0.52	0.69	0.71	0.74
SVC$_{15s}$	1.00	0.69	0.64	0.75	0.77	0.74
DTC$_{15s}$	0.92	0.79	0.70	0.79	0.74	0.75
RFC$_{15s}$	0.91	0.76	0.64	0.76	0.68	0.71
ABC$_{15s}$	0.94	0.75	0.64	0.76	0.63	0.67
GBC$_{15s}$	0.94	0.79	0.64	0.76	0.69	0.71
GNB$_{15s}$	0.81	0.52	0.70	0.79	0.70	0.73
LDA$_{15s}$	0.88	0.70	0.83	0.78	0.71	0.67
QDA$_{15s}$	1.00	0.48	0.64	0.76	0.69	0.71
KNC$_{30s}$	0.91	0.76	0.64	0.78	0.69	0.71
SVC$_{30s}$	1.00	0.69	0.61	0.74	0.77	0.74
DTC$_{30s}$	0.91	0.73	0.69	0.80	0.73	0.74
RFC$_{30s}$	0.88	0.73	0.62	0.76	0.67	0.70
ABC$_{30s}$	0.93	0.73	0.68	0.80	0.73	0.74
GBC$_{30s}$	0.88	0.73	0.67	0.79	0.68	0.70
GNB$_{30s}$	0.71	0.47	0.70	0.78	0.75	0.69
LDA$_{30s}$	0.88	0.70	0.80	0.75	0.65	0.65
QDA$_{30s}$	0.60	0.60	0.34	0.38	0.42	0.42
KNC$_{1m}$	0.91	0.76	0.59	0.74	0.73	0.74
SVC$_{1m}$	0.96	0.67	0.61	0.74	0.77	0.74
DTC$_{1m}$	0.92	0.78	0.66	0.79	0.60	0.65
RFC$_{1m}$	0.89	0.75	0.63	0.78	0.67	0.70
ABC$_{1m}$	0.89	0.74	0.63	0.76	0.73	0.74
GBC$_{1m}$	0.91	0.75	0.65	0.78	0.61	0.66
GNB$_{1m}$	1.00	0.43	0.78	0.74	0.65	0.66
LDA$_{1m}$	0.88	0.73	0.56	0.70	0.71	0.67
QDA$_{1m}$	0.57	0.51	0.54	0.71	0.68	0.69
KNC$_{3m}$	0.92	0.78	0.59	0.74	0.63	0.67
SVC$_{3m}$	0.96	0.69	0.61	0.74	0.77	0.74
DTC$_{3m}$	0.91	0.73	0.64	0.78	0.67	0.67
RFC$_{3m}$	0.91	0.76	0.62	0.78	0.76	0.75
ABC$_{3m}$	0.89	0.74	0.66	0.79	0.74	0.73
GBC$_{3m}$	0.91	0.76	0.62	0.78	0.69	0.71
GNB$_{3m}$	1.00	0.47	0.75	0.75	0.67	0.64
LDA$_{3m}$	0.89	0.78	0.62	0.75	0.67	0.73
QDA$_{3m}$	1.00	0.60	0.53	0.70	0.73	0.67
KNC$_{5m}$	0.92	0.79	0.59	0.74	0.69	0.71
SVC$_{5m}$	1.00	0.70	0.61	0.74	0.77	0.74
DTC$_{5m}$	0.91	0.75	0.57	0.71	0.71	0.67
RFC$_{5m}$	0.92	0.78	0.60	0.74	0.65	0.67
ABC$_{5m}$	0.91	0.76	0.59	0.74	0.70	0.73
GBC$_{5m}$	0.92	0.78	0.58	0.73	0.70	0.69
GNB$_{5m}$	0.95	0.65	0.63	0.74	0.75	0.71
LDA$_{5m}$	0.90	0.79	0.59	0.74	0.69	0.78
QDA$_{5m}$	1.00	0.62	0.58	0.71	0.78	0.71
Positive	47		25		32	
Total	78		78		78	

4.5 / supplement

TABLE VI

WATER BEHAVIOR DETECTION ON AZBIL-7DAY DATASET. (30 MIN/1 DETECT) (FULL VERSION)

	Teeth		Face		Hand		Urinate		Defecate		Shower		Dishes		W-machine		W-Basin	
	P	A	P	A	P	A	P	A	P	A	P	A	P	A	P	A	P	A
KNC_{1m}	1.00	0.99	0.00	0.98	0.16	0.93	0.18	0.94	0.00	0.96	0.06	0.96	0.00	0.97	0.00	0.98	1.00	0.99
SVC_{1m}	1.00	0.99	1.00	0.99	0.18	0.94	0.17	0.95	0.00	0.97	1.00	0.99	1.00	0.98	0.00	0.99	1.00	0.99
DTC_{1m}	0.00	0.98	0.00	0.94	0.14	0.94	0.45	0.95	0.07	0.96	0.07	0.96	0.18	0.97	0.00	0.96	0.00	0.95
RFC_{1m}	1.00	0.99	0.00	0.97	0.17	0.92	0.35	0.94	0.00	0.97	0.00	0.97	0.00	0.98	0.11	0.98	0.00	0.97
ABC_{1m}	0.50	0.99	0.00	0.97	0.14	0.93	0.26	0.94	0.00	0.97	0.00	0.96	0.21	0.97	0.14	0.98	0.00	0.98
GBC_{1m}	0.00	0.98	0.00	0.96	0.14	0.93	0.40	0.95	0.00	0.96	0.07	0.96	0.21	0.97	0.00	0.98	0.00	0.95
GNB_{1m}	0.06	0.86	0.07	0.86	0.12	0.86	0.20	0.87	0.09	0.86	0.08	0.87	0.08	0.87	0.05	0.86	0.01	0.86
LDA_{1m}	0.20	0.97	0.04	0.88	0.17	0.91	0.30	0.92	0.04	0.94	0.22	0.98	0.04	0.88	0.07	0.93	0.00	0.91
KNC_{3m}	1.00	0.99	0.00	0.98	0.03	0.92	0.50	0.95	0.00	0.96	0.00	0.98	1.00	0.98	0.00	0.96	0.00	0.99
SVC_{3m}	1.00	0.99	1.00	0.99	0.06	0.92	1.00	0.95	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00	0.99
DTC_{3m}	0.00	0.97	0.00	0.96	0.15	0.92	0.41	0.94	0.00	0.91	0.04	0.95	0.00	0.97	0.09	0.96	0.00	0.97
RFC_{3m}	0.00	0.98	0.00	0.97	0.12	0.91	0.44	0.95	0.00	0.94	0.00	0.98	0.00	0.98	0.05	0.96	0.00	0.98
ABC_{3m}	0.14	0.98	0.00	0.96	0.16	0.93	0.31	0.94	0.00	0.92	0.04	0.94	0.00	0.94	0.25	0.98	0.00	0.95
GBC_{3m}	0.12	0.98	0.00	0.96	0.13	0.91	0.44	0.95	0.00	0.92	0.03	0.93	0.00	0.98	0.08	0.96	0.00	0.98
GNB_{3m}	0.06	0.86	0.07	0.86	0.11	0.86	0.20	0.87	0.09	0.86	0.08	0.87	0.08	0.86	0.05	0.86	0.01	0.85
LDA_{3m}	0.03	0.93	0.04	0.87	0.11	0.86	0.22	0.88	0.16	0.93	0.33	0.98	0.08	0.87	0.06	0.90	0.00	0.91
KNC_{5m}	1.00	0.99	1.00	0.99	0.04	0.93	0.11	0.93	1.00	0.98	0.12	0.96	1.00	0.98	0.08	0.97	1.00	0.99
SVC_{5m}	1.00	0.99	1.00	0.99	1.00	0.97	1.00	0.95	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00	0.99
DTC_{5m}	0.25	0.98	0.03	0.94	0.09	0.90	0.23	0.92	0.00	0.94	0.00	0.93	0.00	0.97	0.05	0.91	0.00	0.99
RFC_{5m}	1.00	0.99	0.00	0.98	0.24	0.94	0.44	0.95	0.00	0.94	0.17	0.98	1.00	0.98	0.06	0.97	0.00	0.98
ABC_{5m}	0.33	0.98	0.04	0.95	0.14	0.89	0.26	0.91	0.00	0.95	0.10	0.96	0.00	0.98	0.07	0.93	0.00	0.96
GBC_{5m}	0.25	0.98	0.03	0.93	0.26	0.94	0.23	0.92	0.00	0.93	0.00	0.92	0.00	0.98	0.06	0.94	0.00	0.99
GNB_{5m}	0.05	0.86	0.06	0.86	0.12	0.86	0.19	0.86	0.09	0.86	0.08	0.87	0.08	0.87	0.05	0.86	0.01	0.86
LDA_{5m}	0.00	0.97	0.04	0.88	0.12	0.88	0.19	0.88	0.11	0.90	0.40	0.98	0.08	0.89	0.06	0.88	0.00	0.92
KNC_{10m}	1.00	0.99	1.00	0.99	0.27	0.95	0.15	0.91	0.00	0.98	0.25	0.98	1.00	0.98	0.04	0.95	1.00	0.99
SVC_{10m}	1.00	0.99	1.00	0.99	1.00	0.97	1.00	0.95	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00	0.99
DTC_{10m}	0.00	0.97	0.14	0.98	0.15	0.92	0.27	0.92	0.00	0.90	0.00	0.93	0.00	0.98	0.07	0.93	0.00	0.91
RFC_{10m}	0.00	0.98	0.00	0.98	0.15	0.92	0.28	0.92	0.00	0.95	0.33	0.98	1.00	0.98	0.06	0.94	0.00	0.96
ABC_{10m}	0.00	0.98	0.00	0.98	0.15	0.91	0.45	0.95	0.00	0.96	0.14	0.98	0.00	0.98	0.03	0.93	0.00	0.94
GBC_{10m}	0.00	0.95	0.03	0.93	0.13	0.92	0.28	0.92	0.00	0.93	0.00	0.93	0.00	0.98	0.08	0.93	0.00	0.91
GNB_{10m}	0.05	0.87	0.07	0.87	0.11	0.86	0.20	0.87	0.09	0.87	0.08	0.87	0.08	0.87	0.05	0.86	0.01	0.86
LDA_{10m}	0.00	0.97	0.07	0.87	0.12	0.87	0.20	0.87	0.12	0.90	0.06	0.93	0.08	0.90	0.06	0.89	0.00	0.91
KNC_{15m}	1.00	0.99	1.00	0.99	0.27	0.95	0.52	0.95	1.00	0.98	0.22	0.98	1.00	0.98	0.02	0.92	1.00	0.99
SVC_{15m}	1.00	0.99	1.00	0.99	1.00	0.97	1.00	0.95	1.00	0.98	1.00	0.98	1.00	0.98	1.00	0.99	1.00	0.99
DTC_{15m}	0.00	0.98	0.03	0.92	0.12	0.91	0.44	0.95	0.00	0.97	0.00	0.92	0.00	0.98	0.05	0.96	0.00	0.92
RFC_{15m}	0.00	0.98	0.00	0.92	0.12	0.91	0.57	0.96	0.00	0.93	0.04	0.94	1.00	0.98	0.10	0.96	0.00	0.95
ABC_{15m}	0.00	0.98	0.02	0.92	0.11	0.90	0.52	0.95	0.03	0.92	0.00	0.92	0.00	0.98	0.00	0.95	0.00	0.92
GBC_{15m}	0.29	0.98	0.03	0.92	0.11	0.90	0.47	0.95	0.00	0.92	0.00	0.92	0.00	0.98	0.00	0.95	0.00	0.92
GNB_{15m}	0.06	0.87	0.07	0.87	0.11	0.86	0.20	0.87	0.10	0.87	0.09	0.88	0.09	0.87	0.05	0.86	0.01	0.86
LDA_{15m}	0.06	0.87	0.07	0.93	0.13	0.88	0.21	0.88	0.11	0.88	0.07	0.94	0.02	0.91	0.06	0.91	0.00	0.92
Positive	6		6		16		26		10		7		8		4		2	
Total	614		614		614		614		614		614		614		614		614	

4.6 / Water Leakage Detection

C. Water Leakage Detection

In this section, we will explore the effectiveness of water leakage detection models on different temporal densities. Shalun-Dorm dataset was used to training the water leakage detection model, and the Tokyo (August) and Tokyo (October) dataset were used as testset. Minimum, sum, skewness, and kurtosis were used as input features. The results for Tokyo (August) and Tokyo (October) are shown in Tab. III and Tab. IV. The results on trainset (Shalun-Dorm) can be found in Table. VII.

TABLE VII
WATER LEAKAGE DETECTION ON SHALUN DATASET (APRIL). (FULL VERSION)

		4/12	4/13	4/14	4/15	4/16	4/17	4/18	4/19	4/20	4/21	4/22	4/23	4/24	4/25
Samp. Inter.	Detect Inter.	Accu	Accu	Accu	Accu	Accu	Accu	Accu	Accu	Accu	Accu	Accu	Accu	Accu	Accu
House A		Leakage Time: None													
1min	30min	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5min	30min	0.81	0.92	0.88	0.92	0.81	0.94	0.87	0.90	0.77	0.90	0.90	1.00	1.00	1.00
5min	60min	1.00	1.00	1.00	1.00	1.00	0.83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
10min	60min	1.00	1.00	1.00	1.00	1.00	0.83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
30min	180min	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
60min	360min	0.50	0.50	0.50	0.50	0.50	0.50	0.25	0.75	0.50	0.50	0.75	1.00	1.00	1.00
60min	1440min	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
House B		Leakage Time: None													
1min	30min	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5min	30min	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
5min	60min	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
10min	60min	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
30min	180min	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
60min	360min	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
60min	1440min	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.00	0.00
House C		Leakage Time: 2021/4/17 08:02 ∼ 12:06													
1min	30min	1.00	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Precision						1.00								
5min	30min	0.81	0.92	0.88	0.92	0.81	0.94	0.87	0.90	0.77	0.90	0.90	1.00	1.00	1.00
	Precision						1.00								
5min	60min	1.00	1.00	1.00	1.00	1.00	0.83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Precision						0.00								
10min	60min	1.00	1.00	1.00	1.00	1.00	0.83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Precision						0.00								
30min	180min	1.00	1.00	1.00	1.00	1.00	0.75	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Precision						0.00								
60min	360min	0.50	0.50	0.50	0.50	0.50	0.50	0.25	0.75	0.50	0.50	0.75	1.00	1.00	1.00
	Precision						1.00								
60min	1440min	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Precision						1.00								
House D		Leakage Time: 2021/4/18 17:30 ∼ 23:00 and 2021/4/21 07:00 ∼ 11:00													
1min	30min	1.00	1.00	1.00	1.00	1.00	1.00	0.92	1.00	0.98	0.96	1.00	1.00	1.00	1.00
	Precision							1.00			1.00				
5min	30min	1.00	1.00	1.00	1.00	0.98	0.83	0.96	0.92	0.73	0.85	0.94	1.00	1.00	1.00
	Precision							1.00			0.75				
5min	60min	1.00	1.00	1.00	1.00	1.00	1.00	0.71	1.00	1.00	0.79	1.00	1.00	1.00	1.00
	Precision							0.00			0.00				
10min	60min	1.00	1.00	1.00	1.00	1.00	1.00	0.71	1.00	1.00	0.79	1.00	1.00	1.00	1.00
	Precision							0.00			0.00				
30min	180min	1.00	1.00	1.00	1.00	1.00	1.00	0.71	1.00	1.00	0.79	1.00	1.00	1.00	1.00
	Precision							0.00			0.00				
60min	360min	0.75	0.75	1.00	0.75	0.75	0.25	0.50	0.25	0.00	0.50	0.25	0.75	1.00	1.00
	Precision							1.00			0.00				
60min	1440min	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Precision							1.00			0.00				

4.6 / Water Leakage Detection

TABLE III

WATER LEAKAGE DETECTION ON TOKYO DATASET (AUGUST).

		House 1-a		House 1-b		House 2		House 3		House 4		House 5		House 6	
Sample interval	Detect Interval	Prec	Accu	Prec	Accu	Prec	Accu	Prec	Accu	Prec	Accu	Prec	Accu	Prec	Accu
1min	30min	1.00	1.00	0.98	0.50	0.98	0.91	1.00	1.00	0.96	0.80	0.96	0.82	1.00	1.00
5min	30min	0.94	0.89	0.96	1.00	0.98	0.91	0.96	0.80	0.98	1.00	0.92	0.82	0.94	0.88
5min	60min	0.96	1.00	0.96	1.00	0.79	0.80	0.92	0.80	1.00	1.00	0.83	0.67	0.88	1.00
10min	60min	0.92	1.00	0.88	1.00	0.79	1.00	0.83	1.00	1.00	1.00	0.88	0.67	0.88	1.00
30min	180min	1.00	1.00	1.00	1.00	0.62	1.00	0.62	1.00	0.75	0.00	0.88	1.00	0.96	1.00
60min	360min	0.75	1.00	0.50	0.00	0.50	0.50	0.50	0.50	0.50	0.00	0.50	0.50	0.75	1.00
60min	1440min	1.00	1.00	0.00	0.00	1.00	1.00	1.00	1.00	0.00	0.00	1.00	1.00	1.00	1.00
Leakage Time		19:30∼23:59		00:00∼00:30		9:20∼14:30		11:45∼16:45		10:30∼12:30		11:00∼16:00		8:00∼11:30	

TABLE IV

WATER LEAKAGE DETECTION ON TOKYO DATASET (OCTOBER).

		House 7		House 8		House 9		House 10		House 11	
Sample interval	Detect Interval	Prec	Accu	Prec	Accu	Prec	Accu	Prec	Accu	Prec	Accu
1min	30min	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98	1.00
5min	30min	0.94	1.00	0.90	1.00	1.00	1.00	1.00	1.00	0.98	1.00
5min	60min	0.88	1.00	0.92	1.00	0.96	1.00	1.00	1.00	0.92	1.00
10min	60min	0.92	1.00	0.92	1.00	0.96	1.00	1.00	1.00	0.92	1.00
30min	180min	0.88	1.00	0.75	0.67	1.00	1.00	1.00	1.00	0.88	1.00
60min	360min	0.75	1.00	0.50	0.50	1.00	1.00	0.75	0.50	0.75	1.00
Leakage Time		07:00∼12:00		08:00∼13:00		07:00∼12:00		14:00∼19:00		12:05∼17:03	

4.6 / Water Leakage Detection

From the results we found that the accuracy of 5 min sampling interval combined with 30 min detection, 60 min sampling interval combined with 360 min detection, and 60 min sampling interval combined with 1440 min detection during the training phase is low. Furthermore, we have the highest accuracy with a sampling interval of 1 minute and a detection time of 30 minutes. Similar results can be found in the Tokyo (August) and Tokyo (October) datasets. Therefore, we recommend using a 1-minute sampling interval with 30-minute detection for better accuracy, or a 10-minute sampling interval with 60-minute detection for acceptable accuracy, but with lower power consumption for the SWM.

4.7 / Experiment Conclusions

D. Experiments results

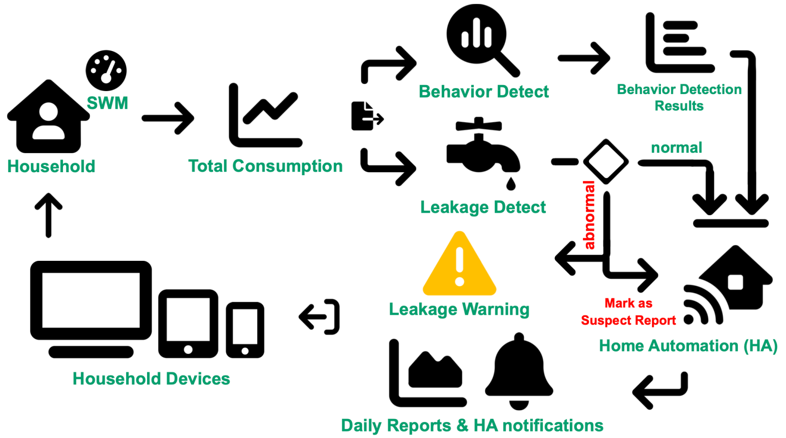
Based on previous results, we combined an SVC model of 5-minute sampling interval with 30-minute water usage behavior detection and a DBSCAN model of 5-minute sampling interval with 60-minute water leak detection as our framework model. Several services referred in Sec. III will be provide based on this setting. Note that once the water leak detection alarms, the detection of water behavior during that time period will be considered an unreliable analysis.

05
Conclusions

5.1 / Conclusions

V. CONCLUSIONS

In this work, we proposed a SWM based energy-efficient home automation framework to save energy and improve quality of life. In experiment results, We can find that water behavior and leaks can be notably detected using only the total water consumption value. In summary, we make the following three main contributions. First, we evaluate the possibility of detecting water behavior using only total water consumption values. Second, we explore the effect of using different temporal densities. Third, we combine the water leak detection system with the water behavior detection system to make more credible reports. We conclude that this study may provide useful information for those designing SWM-related systems.



06
Acknowledgment

6.1 / Acknowledgment

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Document Version:

Water Detection and Monitoring Service for Energy-Efficient Home Automation

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Abstract— **Energy efficiency and home automation are becoming increasingly important. In this study, we design an energy-efficient home automation framework based on smart water meters (SWM) to save energy and improve quality of life. Through the proposed approach, various services including stay-up alarm, post-laundry weather forecast, insufficient water intake alarm, daily water behavior report, and water leak alert can be provided. More specifically, we will use a single SWM to collect total water consumption to detect household water use behavior and leaks. Nonetheless, to prevent unnecessary electronic usage for SWMs, we also explored the relationship between effectiveness and different temporal densities. Therefore, the SWMs in the design system do not have to collect and send usage information every second, but still have similar accuracy and precision.**

Index Terms: Smart Water Meter, Home Automation, Water Leakage Detection, Water Behavior Detection

I. INTRODUCTION

Since the invention of the home smart meter, energy usage analysis has been considered not only in the factory but also in the home. Therefore, many studies based on smart meters have been proposed. Some researches use electricity smart meters (ESM) to reveal household characteristics [1, 2]. Some researches have explored the relation between ESM and integrated energy system [3]. Some researches aim to protect user privacy. Notable examples include [4, 5]. Some researchers provide a conplete view, including anomaly detection, load forecasting, consumer segmentation, and demand response [6].

Not only electricity, but smart water meter (SWM)-based research is also increasing notably. Some researches build water management system with SWM [7]. Some researches provide a solution for connecting SWM to Internet of things (IoT) environment. Notable examples include [8, 9]. Some focus on reducing the electricity usage of a SWM [10, 11]. Some focus on detecting water leakage [12].

In this work, we will only focus on water domain.

With growing concerns about energy shortages, energy efficiency has become increasingly important in recent years. Everyone is be responsible for conserving water. However, most of us don't notice how many water conservation we do everyday. Similar problems have been found in smartphones. If we want to spend less time on our smartphones but we don't know which apps take the most times, we can simply see how much time we spend on each app by checking the weekly screen time report. Therefore it would be useful for us to reduce our water usage if we had daily and weekly water usage reports like our smartphone's weekly screen time reports. To achieve this, we need to analysis data from SWMs. The best way to analysis household water consumption is to install multiple SWMs on different devices. We can then get usage information for every machine in the home and provide an accurate daily report of water usage. However, those who are struggling or living in older homes may be reluctant to incur the cost of installation and maintenance. Therefore, we explored the possibility of building energy-efficient homes using a single SWM for those who only have a smart meter for total water consumption. In addition, since water leakage problems can affect the accuracy of water behavior detection and waste water, we combine the water leakage detection model with the daily water consumption report in the proposed system.

As data is sent more frequently, smart meters will require more power. To reduce the electricity consumption of SWM, we also explored the relationship between effectiveness and different temporal densities for both water behavior detection and water leakage detection.

Furthermore, since we can detect water use behaviors, we can also provide home automation services. Overall, we will combine water behavior detection, water leakage detection, and home automation services in our work.

II. RELATED WORKS

A. WATER LEAKAGE

In the water leakage detection experiment, we adopt the water leakage detection algorithm proposed by Lo-Paug-Yun Ting[†] as our water leakage detection model. The algorithm is based on Density Applied Spatial Clustering with Noise (DBSCAN) combined with some rule-based models. However, the framework is based on a fixed temporal density, so we will retrain the model with different sample and label intervals to explore the relationship between effectiveness and different temporal densities.

III. WATER DETECTION AND MONITORING SERVICE FOR ENERGY-EFFICIENT HOME AUTOMATION

In this section, we divide the problem into five parts: water behavior detection, water leakage detection, combination of water behavior and leakage detection, home automation, and the whole system we proposed.

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lish useful post-laundry weather forecasts. Once the system detects that the user is using the washing machine, it sends weather forecast information for the next 12 hours to help the user decide whether to hang out the clothes or use the dryer.

Fig. 1. System strcture

TABLE I
BRIEF OF WATER BEHAVIOR ON AZBIL-5DAY DATASET. (15 MIN/1 DETECT)
FULL RESULTS CAN BE FOUND IN TABLE. V

	Toilet		Kitchen		W-Basin	
	Prec	Accu	Prec	Accu	Prec	Accu
SVC_{1s}	1.00	0.69	0.64	0.75	0.77	0.74
SVC_{15s}	1.00	0.69	0.64	0.75	0.77	0.74
SVC_{30s}	1.00	0.69	0.61	0.74	0.77	0.74
SVC_{1m}	0.96	0.67	0.61	0.74	0.77	0.74
SVC_{3m}	0.96	0.69	0.61	0.74	0.77	0.74
SVC_{5m}	1.00	0.70	0.61	0.74	0.77	0.74
Positive	47		25		32	
Total	78		78		78	

3) insufficient water intake alarm: Since we can detect and record the number of times a user urinates per day, we can alert at the end of the day if the number of urinations in a day is less than 70% of the historical record.

E. Energy-saving home automation

As we mentioned in Sec. [**sec:intro**], if we provide daily and weekly water usage report to users, they might aware the water usage and reduce the unnecessary water behaviors. Also, several interest home automation which we mentioned above can be provide.

More specific, we will collect data with SWM and send it to local or remote server to detect behaviors. Once the events occur, server will send notification to user's phone, iPad, and smart TV if they have. Events include stay-up alarm, post-laundry weather forecast, insufficient water intake alarm, daily and weekly water behavior reports, and so on.

System structure is in Fig. 1.

IV. EXPERIMENTS

A. Model architecture

We used a variety of traditional machine learning methods to evaluate the effectiveness, including K-Neighbors Classfier (KNC), Support Vector Classifier (SVC), Decision Tree Classifier (DTC), Random Forest Classifier (RFC), AdaBoost Classifier (ABC), Gradient Boosting Classifier (GBC), Gaussian Naive Bayes (GNB), and Linear Discriminant Analysis (LDA). The KNC uses 5 neighbors and uniform weight. The SVC uses rbf kernel and scale gamma. The DTC uses Gini

Google Drive Link:
https://drive.google.com/file/d/1WPybEvlx89veoKVu1N8FHaRFLA40lFUG/view?usp=sharing

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