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Optimization of Power Usage in a Smart Nursing Home Environment

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***Abstract*—This article presents a case study of using self-cognizant prognostics for the management of three key areas in a nursing home where a substantial proportion of power consumption is spent in a typical nursing home environment. Using a power-efficient monitoring system, our case study covers smart lighting, air conditioning and meal preparation; which is aimed at reducing the cost of operation through more efficient use of energy with smart and assistive technologies. The results show an overall enhancement of approximately 10% in energy efficiency while offering a safe environment for elderly patients in a smart nursing home.**

***Index Terms*—Elderly care, energy efficiency, self-cognizant prognostics, smart buildings**

I. Introduction

THE cost of energy that include electricity and natural gas contribute towards a substantial portion of the operational cost for a typical nursing home. In particular, elderly patients are more prone to variation in temperature that can potentially trigger a number of medical conditions [1]. Temperature regulation alone consumes a very substantial amount of power all year round [2].

In the smart city context, optimizing energy efficiency is an important aspect in many parts across the smart city infrastructure, examples like transport system [3] and lighting system [4]. The latter specifically tackles the implementation challenges with interoperability and this is an important design consideration in a smart nursing home where several sub-systems work together to serve elderly residents. Another important factor is an optimal balance between the cost and value in elderly care [5]. The situation concerning nursing homes differs from premises like regular homes and offices in that simple energy saving mechanisms such as motion-based lighting sensors are inappropriate due to safety reasons. In this example, the lights must be switched on shortly before an elderly person enters as an accident prevention measure. Contrary to the simple motion-based sensors, lighting system that yields energy saving must also provide elderly residents adequate illumination for accident prevention [6].

Addressing the issue associated with optimizing energy efficiency in a nursing home such that the operating cost can be lowered, this paper proposes a smart power management system through a self-cognizant prognostic approach [7]. Optimizing power consumption entails on site assessment of different parts of the facility during different times of the day as well as any seasonal patterns throughout the year [8]. One of the main objectives is to develop a system that minimizes energy consumption without compromising on safety. The paper is organized as follows: Section II provides an overview of the problems associated with energy efficiency in a smart nursing home setting followed by the design and implementation of a self-cognizant power monitoring and management system in Section III. Overall system operation for power optimization is presented in Section IV and a summary of contributions is concluded in Section V.

II. Smart Nursing Home Problem Overview

To analyze power usage in relation to the operating cost of a nursing home, we look at the layout of a nursing home that serves up to 90 elderly residents with a maximum staff to resident ratio of approximately 1:4. Our main objective is to enhance the operational efficiency of the nursing home by optimizing power usage. Power consumption is analyzed by using data-driven prognostics that integrates usage pattern recognition with a spatial-temporal dynamic statistical model for utilization prediction that takes into consideration seasonal patterns such as heating and air-conditioning during winter and summer months [9]. The proposed self-cognizant methodology devises a machine-learning framework with the study of three main areas across the nursing home. For the purpose of identifying areas of substantial power usage, we link all special assistive support apparatus to the smart lighting system where apparatuses are usually used when the lights are also operating at the same time [10].

In addition to illumination, air conditioning system that entails both ambient temperature and indoor air quality (IAQ) control is another area that use a substantial amount of electricity. The meal preparation sub-system is more complicated than the other systems outlined above in that it uses both electricity and natural gas as energy sources. For this reason, the laundry sub-system is also linked to the meal preparation system as dryers are also operated on natural gas.

Power utilization across the nursing home is made smarter

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through the development of a spatial-temporal dynamic monitoring approach for the power usage modeling, with a data-driven approach that learns power consumption, followed by the implementation of a Bayesian analysis method for self-updating of data-driven statistical model that dynamically adjusts to any environmental or operational changes over time. This takes into consideration variations such as ambient environment and number of residents. Self-cognizant prognostics methodology is designed to eliminate the dependence on models derived from traditional smart meters making power management adaptive to variations due to other uncontrollable factors such as component aging and degradation or variation of a given system's operational conditions that may cause power usage to be less efficient [11].

The power usage data across the nursing home from smart meter is analyzed as prognostics data [12]. There is a strong need for a major change in power consumption assessment as well as identification of areas where wastage can be cut across smart buildings, and prognostics that entails the real-time prediction of power consumption. There is also a special need to address power savings through switching off unused apparatus without compromising safety. Thus, the proposed prognostics-based power optimization scheme is a new approach whose design goals include effective and efficient smart control for various systems that continuously monitor power consumption themselves, that are self-cognizant using algorithms that fuse sensor data, analyze historical power usage data from smart meters and generate false alarms for areas with power wastage identified, correlate faults with relevant system events and and predict surge of power usage in advance.

To optimize energy efficiency, a management system is needed to monitor power usage of each of these systems as well as the sensing network that gathers information about the nursing home environment and co-ordinate the operation of various systems.

III. Self-Cognizant Prognostic Power Management

Addressing the grand challenge of optimizing power usage across a smart city, various artificial intelligence (AI) and big data analytics techniques have been developed in making smart grids more efficient [13]. To carry out power usage assessment for subsequent optimization, the process entails several complex steps in deriving analysis strategies as well as implementation decisions [14]. The process also involves statistical modeling and drawing inference from power usage data through extraction of meaningful patterns from a set of observations to suggest where within a particular building that power usage can be reduced while at the same time not compromising on health and safety.

As there are practical problems with handling a huge amount of data points collected from our test lab and sites, using data reduction methods as pre-processing is essential. In this research, we develop a new data reduction method based on density-based techniques to assess the energy consumption of different areas within the building [15]. So in addition, we have conduct assessment on energy demands from different sections of the nursing home.

With the energy consumption of various sections profiled, it is possible to apply a self-cognizant algorithm for energy optimization through a prognostics approach. The power management model is shown in Fig. 1 where the core parts consist of a wireless sensing network (WSN) and input from the smart power meters. The WSN gathers important information about the location of nursing home residents, staff members as well as areas that are vacant so that energy saving measures such as dimming the lights and air conditioning can be adjusted accordingly.

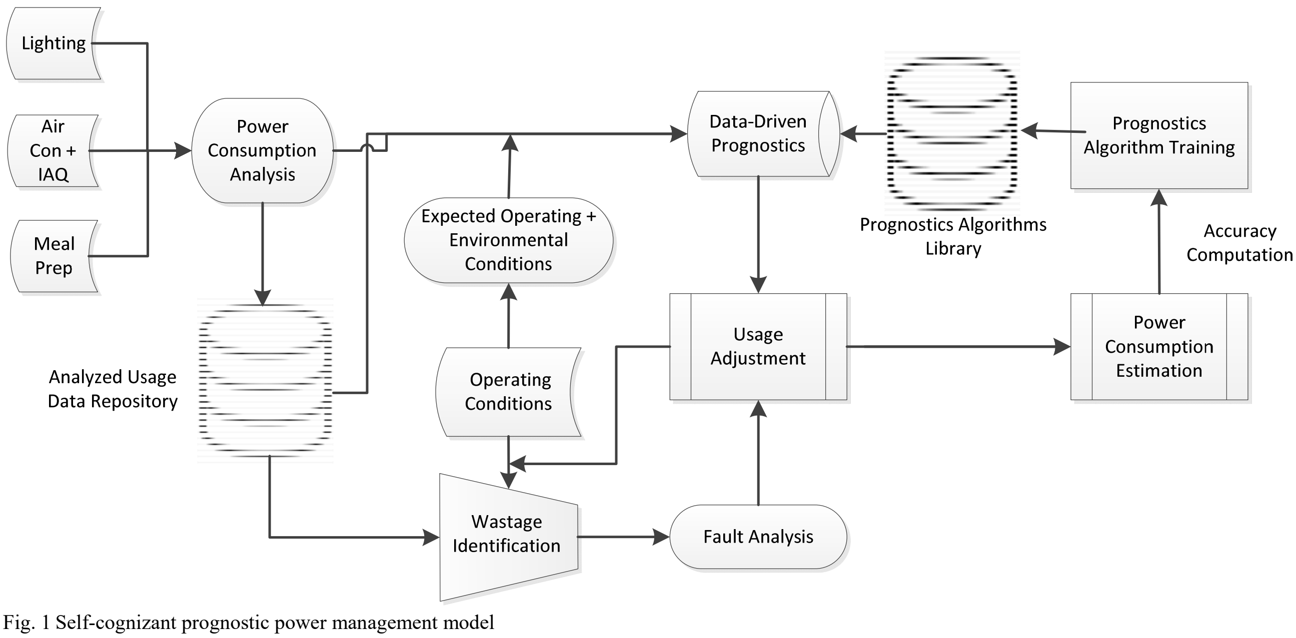

Fig. 1 Self-cognizant prognostic power management model

A. Lighting

Smart lighting control in a nursing home primarily concerns balancing residents saving and minimizing the time of lights being switched on when not needed. The lighting system entails far more than motion sensors for lighting control. In the nursing home environment where elderly residents often have some form of visual impairments, ordinary motion sensors are inadequate due to risk of falls [16]. Location tracking of individual residents is accomplished using the active RFID system presented in [17]. With profiles of each resident's health conditions, it is then possible to develop a motion recognition system that caters for individual conditions such as visual or mobility impairment. Using methodologies such as Long Short-Term Memory Network (LSTM) and Convolutional Neural Network (CNN) proposed in [18] can be used for feature extraction from a lidar-based feature extraction system. The objective of such system is to balance between power consumption and illumination for individual elderly resident. Based on different activities, that can include different people in the same area within the nursing home as well as the same elderly resident moving across different areas, there are two modes of recognition as either cross-person or cross-area recognition. These modes require that both the training set and the testing set are mutually exclusive in the dataset. One of the major implementation issue is that [19] reported a substantial reduction in performance over the cross-person recognition mode with its accuracy drops from 96% to 73% when a fifth person enters the system as the testing set. To address this performance degradation issue, we commence by analyzing the set of cross-person and cross-area experimental data with a comparison of feature distributions in two sets of experiments.

These feature distributions in cross-person and cross-session experiments correspond to the outputs of the penultimate fully connected layer that uses a pooling layer in conjunction with each convolutional layer, which consists of contains 32 filters of size (5,5) using a Parametric Rectified Linear Unit (PReLU) deployed as in [20]. A classifier that possess generalized ability such that feature extraction is carried out within a class since the classifier exhibits similar feature distributions on both the training as well as the test datasets. The classifier is unaffected by the unknown source labels for feature representation. In cross-person (session) recognition, the test dataset shows a certain degree of divergence in part of the test features that possesses similarities to the training set distribution.

An associative classification proposed in [21] provides adequate generalized ability exhibits similar feature distributions on the training and testing sets. The extracted features are then collected in the class such that the intra-class feature distributions for assessing the distributions under the influence of unknown source samples in the training set can be computed. This is an important assessment when the system senses unregistered persons such as visitors. The results indicate that both recognition modes have the intra-class features distribution changes. The distribution changes of intra-class features are fairly similar in both recognition modes such that the corresponding features extracted are divergent while the classifier has no prior knowledge on the properties of the source characteristics and convergence can be observed such that features extracted from remaining samples as some knowledge about the source characteristics are became known to the classifier. Such observation indicates that the classifier can learned the subject movement performing characteristics that is embedded in the movement signal.

Dynamic motion analysis that detects gait and posture information within a frame is processed through data augmentation [22]. Range doppler map (RDM) is then used for gait and posture recognition using lidar and acquires discriminative information [23]. This map consists of a sequence of range verses walking velocity plots, such that the maps reveals the reflected energy from a person with different intensity values, data augmentation is implemented from across a frame sequence over $time_f$ in the motion sequences, such that, for example, when a person walks across the corridor the entire map is composed of N frames. A resultant range doppler map with its i-th frame is the sum of the first i raw map within the sequence of maps, as shown in Eq. (1):

$$eRDM_i = RDM_i + RDM_{i-1} \quad i \in [1, 2, \dots, N] \tag{1}$$

where $eRDM_i$ is the i-th frame of the resultant range doppler map that has been enhanced, and RDM_i is the i-th raw range doppler map. Combining the posture signals' characteristics when a user walks, a non-coherent accumulation from frame to frame is analyzed through the posture sequences. Such that the complete trip made by the user that walks around the nursing home contains a total of N frames of RDM, the i-th frame of *eRDM* would be the sum of the first i number of raw RDMs. The data augmentation mechanism preserves the walking movement information from one frame to the next, such that it reduces the impact of anomaly frames on movement analysis. Increasing the frame index can yield more comprehensive movement information within the resultant range doppler map that in turn yields a higher degree of recognition confidence, thereby increasing the accuracy of motion tracking for a given person. Fig. 2 shows a sequence of RDMs that represents a posture sequence over a certain period of time, the horizontal axis of RDM represents the velocity at which the user walks at the instance of a given frame being captured, whereas the vertical axis represents the range. The different brightness in RDM conveys information about the reflected energy with the respective intensity values.

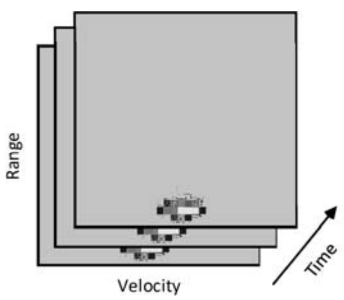

Fig. 2 Range Doppler Maps (RDMs) sequence structure

The second training phase helps focus on generalization by utilizing data augmentation for feature representation [24]. Similarities in gait and posture between different persons can be assessed within the intra-class variant movement. For example, two different persons that use crutch on the right hand side would exhibit very similar features within a class that enhances identification accuracy. Focus on generalization error is analyzed to identify the similarities among different personalized samples, that utilize aggregated intra-class salient features irrespective of the source of data. A motion sample that corresponds to an associated category label and a source label that represent the person labels in cross-person recognition and the area labels in cross-area recognition, are used to compute the focus on generalization error. These labels act as precursors for the analysis of gait and posture. The category labels are used for classification whereas the source labels are used for error calculation. The feature distance determines the convergent features within a class hence should be minimized.

The difference between different persons, as inter-source difference, as well as the difference in gait and posture, as in intra-source differences will need to be computed to yield feature convergence of the same category and source with an intra-source error of E_{Intra}. Whereas E_{Inter} is computed to ensure feature convergence of different sources within the same category such that:

$$E_{Intra} = \frac{1}{2}\sum_{i=1}^{n} \left| f^{i}_{ci,si} - \bar{f}_{ci,s1} \right|^2 \tag{2}$$

$$E_{Inter} = \frac{1}{2}\sum_{ij}\sum_{k} || \left[1 - \delta(s_k = s_0) \left(\bar{f}_{cj,sk} - \bar{f}_{cj,s0} \right) \right] ||^2 \tag{3}$$

Error calculation is based on a total of n samples and the i-th feature that contains a pair of category c and source s labels. These are used for computing the discriminative features so that the frames can be enhanced to be fed into the recognition model under the constraints of the focus on generalization error. The main purpose of this recognition model as shown in Fig. 3 is for extraction of generalized discriminative features with a connected layer for feature extraction. It consists of two convolutional layers and followed by pooling of each layer. The outputs of the last two connected layers yield the focus on generalization error.

In the initial trial run, a deep model with a classifier such that the operation shown in Fig. 3 entails Conv 1 = 32 filters of size (5; 5) | *stride =1; padding =2*, Conv 2 = 64 filters of size (5; 5) |*stride=1;padding=2*, Conv 3= 128 filters of size (5; 5) | *stride =1; padding =2* and the two FCs are 64 followed by 2.

B. Temperature and Indoor Air Quality Control

The ambient environment has a substantial impact on both the health and safety of nursing home residents. In particular, ambient temperature variation can have a substantial impact on component durability as well as energy efficiency. Electronic component life cycle loads can be significantly affected by operating environmental conditions such as temperature, humidity, vibration, shock, utilization duration and frequency that make power usage of air conditioners particularly unpredictable in certain parts of the nursing home.

In addition to temperature control, indoor air quality (IAQ) is another important parameter that needs to be regulated. These include carbon monoxide (CO) sensing and pollution control that is particularly important for COPD patients [25]. The idea of optimizing energy efficiency for both temperature and IAQ control commences by analyzing the concentration of people in a given section of the building [26]. Profiling section by section within the nursing home building is accomplished by an active RFID tagging system derived from [27], where patients with washable tags embedded in smart clothing as well as tags carried by staff members as well as visitors are tracked for the purpose of their whereabouts. Such profiling of crowds within a given section provides prognostics information about the necessity for temperature and ventilation adjustments in conjunction to fused data from in-room temperature and air quality sensors.

In a typical RFID system deployment, there is at least one of a reader and multiple identification tags. Each tag is embedded in the smart clothes conveys certain information about the patient [28]. The likelihood of a tag collision increases when the number of tags within a given area increases.

In the most primitive implementation, Framed Slotted Aloha (FSA) reading process uses Markov chain to derive the optimal frame length [29]. The frame length is dynamically adjusted according to the number of remaining tags in Dynamic FSA.

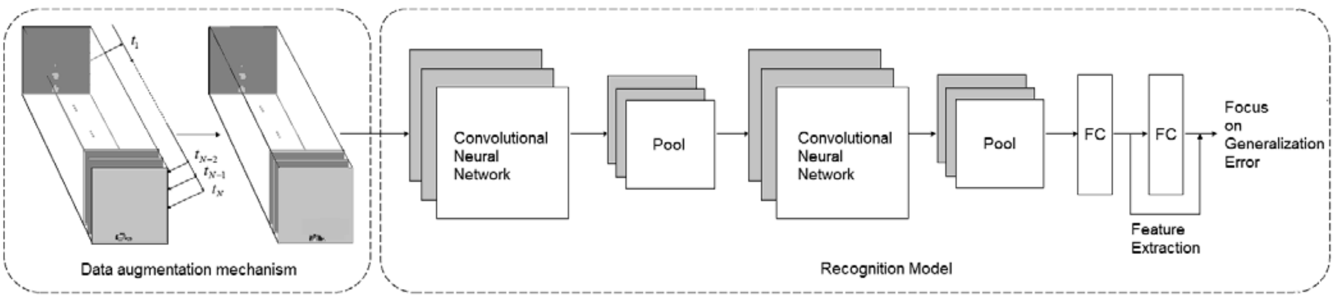

Fig. 3 Recognition model architecture

Estimation of the number of remaining tags would allow the length of the next frame to be adjusted accordingly. Identification cycle is the process of identifying all the tags within the RFID tag reader coverage area [30], which consists of multiple frames. Upon successful identification of the first frame, the initial tag population size is estimated from the number of tags identified within the first frame.

The initial tag population size estimation algorithm is computed between the first and the second frame through initial tag population size estimation and subsequent removal of the pseudo size value. The tags that have been successfully identified are subtracted from the second frame. The current frame length is optimized for the number of the remaining tags. The process is repeated for subsequent frames until all tags within range are successfully identified. This linear interpolation estimation algorithm solves a transcendental equation, which yields a pseudo value that is subsequently subtracted. In the case where the number of estimated tags far exceeds that of the number of actual tags, $QN + 1$, i.e. length of the next frame, will be larger than the actual number of tags within the area. Adjustment of frame length will thus result in the increase in idle slots, thereby reduces the identification efficiency. Conversely, if the number of estimated tags is much smaller than the number of actual tags, Q becomes smaller than the number of tags to be identified, thereby increases of probability of a tag collision.

Upon completion of the first frame, the linear interpolation algorithm is utilized to solve the nonlinear transcendental equation to estimate the initial tag population size according to the number of successfully read slots. The number of remaining tags can therefore be estimated through subtracting the number of tags successfully identified within the frame. The length of the next frame can then be adaptively adjusted for enhanced identification. The length of the subsequent frame is identical to the number of remaining tags for global optimal identification through the following process:

Step 1: Broadcast command Query(Q) as the reader commences frame #1 of length Q_1;

Step 2: Upon reception of command Query(Q), each tag generates a random number RC_i, in response to the reader;

Step 3: Broadcast command *ReadID* as a slot commences at the reader;

Step 4: Upon reception of command *ReadID*, each tag subtracts RC_i by 1. Tags with $RC_i = 0$ respond to reader while other tags ($RC_i \neq 0$) wait for the next slot;

Step 5: The reader reads with slot *IdN*, when only one tag responds to reader;

Step 6: The reader estimates the number of initial tags $\hat{n}$ from *IdN*.

A simple state machine for tag state transition is shown in Fig. 4 that consists of three states with accompanying conversion logic [31]. In the Active state, a tag will enter the Period Silence state when it is successfully read by the reader. Conversely, a tag enters the Frame Silence state upon a collision while responding to the reader.

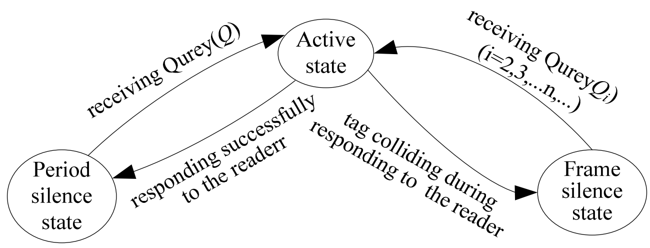

Fig. 4 Tag state transition

The probability that r tags occupy one slot is with number of n tags being identified based on a uniform distribution such that:

$$P(Q,n,r) = C_n^r \times \left(\frac{1}{Q}\right)^r \times \left(1-\frac{1}{Q}\right)^{n-r} \tag{4}$$

Further, the probability that only one tag being successfully read is:

$$p(Q,n,1)_1 = \frac{1}{Q}(1-\frac{1}{Q})^{n-1} \tag{5}$$

The expected value for all subsequent $Q_{2,3,\ldots,n}$ tags with Q_e successful slots out of Q slots is thus:

$$Q_e = \frac{n}{Q}(1-\frac{1}{Q})^{n-1}Q = n(1-\frac{1}{Q})^{n-1} \tag{6}$$

The estimated value $\hat{n}$ can be computed by solving Eq. (6) from substituting successful slots *IdN* from Q_e after the first frame such that:

$$f(x) = x(1-\frac{1}{Q})^{x-1} \tag{7}$$

Consider *IdN* as a function of integral value x, i.e. $f(x)$=*IdN*. This yields $\hat{n} = round(x)$ as Eq. (7) is a continuous function of x between x_l and $x_u \in (0,\infty)$, such that:

$$\frac{f(x_{S,l})}{x_S - x_{S,l}} = \frac{f(x_{S,u})}{x_S - x_{S,u}} \tag{8}$$

$$x_S = x_{S,u} - \frac{f(x_{S,u})(x_{S,l} - x_{S,u})}{f(x_{S,l}) - f(x_{S,u})} \tag{9}$$

With either $x_{S,l}$ or $x_{S,u}$ being substituted for x_S under repetitive iteration, solving Eq. (10) will result in a solution within the interval between $x_{S,l}$ and $x_{S,u}$. The interpolation algorithm will proceed as follows:

Step 1: Determine lower bound $x_{S,l}$ and upper bound $x_{S,u}$: $f(1) < f(x_S) < f(Q)$, set initial value as $x_{S,l}$=1 and $x_{S,u}$=Q.

Step 2: Initial estimation

$$x_S = x_{S,u} - \frac{f(x_{S,u})(x_{S,l} - x_{S,u})}{f(x_{S,l}) - f(x_{S,u})}.$$

Step 3: Compute and compare function $f(x)$ so that:

If $[f(x_{s,l}) - IdN].[f(x_s) - IdN] < 0$, $x_{s,u} = x_s$;

Then repeat Step 2;

Else $[f(x_{s,u}) - IdN].[f(x_s) - IdN] < 0$, $x_{s,l} = x_s$, proceed to Step 4.

Step4: Determine completion: If $[f(x_{S,u})\text{-}IdN] \cdot [f(x_{S,l})\text{-}IdN] = 0$, or $|x_{s,l} - x_{s,u}| < \varepsilon_{Th}$, terminate the iteration. With ε_{Th} being the threshold to be determined by the required accuracy.

The simulation results of linear interpolation are listed in Table I. Two solutions exist for each Q_e, one of which is a pseudo size value that can be eliminated. The maximum relative-error is 1.29% and the maximum number of iterations are 12. When n=1000, the two solutions are 1000 and 1002 which yields a 0.2% error under a maximum of 2 iterations. These simulation results are derived from Q_e as the function value. Simulation result on iterations of the initial tag population size computed using linear interpolation upon completion of the first frame by substituting IdN for Q_e is shown in Table II. It shows a relative error of for first test is 7.2%, the error is significantly reduced to below 1.5% for all subsequent tests when number of iterations does not exceed 10.

There are two solutions for each IdN when a significant difference between n and Q exists. One of which is a pseudo size value that needs to be removed. Based on the simulation results of Tables I and II, two solutions, n_S and n_B, are obtained after the first frame. Where n_S is less than the optimal value and n_B is greater than the optimal value.

TABLE I
LINEAR INTERPOLATION SIMULATION RESULTS

n	Q_e	LoS	Iteration sequence and corresponding approximation solution $\hat{n}$ 1	2	3	4	5	6	7	8	9	10	11	12	AE	RE	IT
100	91	$\hat{n}_S$	246	116	102	101	101	—	—	—	—	—	—	—	1	1%	5
		$\hat{n}_B$	7783	6151	5021	4326	3963	3804	3741	3719	3710	—	—	—	PS	PS	11
400	268	$\hat{n}_S$	728	554	466	427	410	404	400	—	—	—	—	—	0	0%	7
		$\hat{n}_B$	3450	1948	2035	2020	—	—	—	—	—	—	—	—	PS	PS	4
700	348	$\hat{n}_S$	945	895	851	815	785	763	746	733	724	717	713	709	9	1.29%	12
		$\hat{n}_B$	1491	1305	1366	1372	—	—	—	—	—	—	—	—	PS	PS	4
1000	368	$\hat{n}_S$	1000	1000	—	—	—	—	—	—	—	—	—	—	0	0%	2
		$\hat{n}_B$	1002	—	—	—	—	—	—	—	—	—	—	—	2	0.2%	1
		$\hat{n}_S$	962	926	893	864	839	819	802	789	779	771	765	760	PS	PS	12

TABLE II
INITIAL TAG POPULATION SIZE ESTIMATION

n	*IdN*	LoS	Iteration sequence and corresponding solution $\hat{n}$ 1	2	3	4	5	6	7	8	9	10	AE	RE	IT
100	90	$\hat{n}_S$	243	115	101	99	99	—	—	—	—	—	1	1%	5
		$\hat{n}_B$	7808	6188	5059	4359	3990	3825	3759	3735	3726	3723	PS	PS	10
400	268	$\hat{n}_S$	728	554	466	427	410	404	401	—	—	—	1	0.25%	7
		$\hat{n}_B$	3450	1948	2035	2020	—	—	—	—	—	—	PS	PS	4
700	343	$\hat{n}_S$	932	870	818	777	746	722	706	694	686	681	9	1.29%	10
		$\hat{n}_B$	1614	1330	1413	1422	—	—	—	—	—	—	PS	PS	4
1000	368	$\hat{n}_B$	1026	1049	1064	1072	—	—	—	—	—	—	72	7.2%	4
		$\hat{n}_S$	1000	1000	—	—	—	—	—	—	—	—	0	0%	2
		$\hat{n}_S$	964	931	900	873	849	829	813	800	790	781	PS	PS	10

The reader broadcasts command Query(Q_S) to all tags. Tag_i (i=1,2,..., n) generates a random number $RS_i \in [1, Q_S]$ as the designated slot to which it sends data back to the reader. Tag_i also generates a random number PS_i of length u as the substitution for the ID code to minimize the time overheads. After sending the Query(Q_S) command, the reader sends the command *NextSlot* to all tags slot by slot. Upon receiving the *NextSlot* command, Tag_i subtracts 1 from RS_i until $RS_i = 0$, indicating that Tag_i responds to the reader. Tags with RS_is > 0 will waits for the next *NextSlot* command. The reader counts the number of successful tags, *NS*, according to tag response. The same methodology is applied for processing the Query(Q_B) command to obtain the number of successful tags *NB*. n_B is regarded as a pseudo size value when $NS \geq NB$.

C. Meal Preparation

Meal preparation that caters for both nursing home residents and staff members consume a substantial amount of energy. This sub-system mainly covers the catering facility and also includes water boilers. The dietary and softness requirements are particularly problematic in the nursing home environment where certain patients might have a wide range of issues such as chewing and risk of chocking [32].

This part on energy consumption for meal preparation is simpler than the previous two parts discussed due to the fixed-time daily schedule. Traditional energy usage prediction methods for commercial kitchens assume that cooking is carried out with a fixed daily schedule [33], such usage prediction models would have would have substantial fallacies due to the varying needs of meals among elderly patients in a nursing home environment [34]. In particular, the schedule for meal preparations is known to not be constants even though a daily pattern exists, like there are breakfast, lunch, tea and supper that make up for four times daily. Also, because the models require a significant amount of data associated with the type of meals, they tend to be outdated as soon as they are developed. In addition, none of the energy usage prediction methods identify what types of special meals are required to cater for patients with eating problem due to various health problems or mechanisms for balancing dietary needs, nor do they include any uncertainty analysis that could potentially lead to a significant wastage of both food and energy [35]. Furthermore, they all provide completely different results for any given cooking facility subject to given conditions. An alternative prognostics-based approach for optimizing energy consumption in a smart nursing home is therefore proposed.

Prognostics approach utilizes the idea that the energy consumption could be determined and that the types of meals needed for both patients and staff members of the nursing home could be predicted on an in-situ session-level basis using known data about individual health requirements. The model is to use in-situ health and daily activity data to predict the type of meals needed by an individual person (or, in some cases, the number of additional meals required). Modeling and drawing inference from fulfilling meal requirements requires extraction of meaningful information from a set of observations about patients as well as staff members. To achieve this goal, our prognostics algorithm utilizes data reduction methods as pre-processing to categorize mainly into regular and soft meals, where the latter is more uniform in terms of the associated energy consumption for preparation.

Principal Component Analysis (PCA) is most appropriately used for representing data after dimension reduction [36]. In classifying meals to be prepared for a particular session, the support vector machines (SVM) is well-known for its classification ability that relies on preprocessing the data in a high dimension. As a result, SVM tends to be less prone to problems of overfitting than some other classifiers [37]. SVMs are especially suited to analyze data with unknown or non-linear distributions as a supervised technique that is useful when patients' health and daily activities information are available.

Anomaly detection is other key task in prognostics for energy efficiency enhancement in meal preparation, such anomaly addresses the fluctuations in meal demands for special occasions such as a reduction in number of patients present or additional demands are needed for visitors. While the classification task focuses on minimizing the misclassification of various discriminating states, the anomaly detection task focuses on minimizing the time-delay of detecting such variations subject to a controllable false alarm, implying that the variations in meals demand may not be significant. We make use of statistical process control (SPC) methods, being one of the widely used techniques for process monitoring and change detection in manufacturing applications [38], to detect the occurrence of special cause variations. The control chart of SPC is useful to prognostics implementation in that it is able to monitor in-situ the performance of the concerned components over time.

IV. Implementation and Analysis

The baseline of energy consumption is set as the three consecutive months of the previous year without any power management scheme deployed. Historical data also provides important insights into profiling the energy usage of different sub-systems within the smart nursing home.

This self-cognizant approach applies multivariate monitoring techniques to the extracted features that include projections, transformations, and metrics statistics such as centroids. It takes into consideration the correlations among feature parameters to detect changes in energy consumption efficiently and accurately. Changes in metrics that are indicative of any wastage or otherwise can be more efficiently used are the precursors to adjusting certain parameters within the nursing home power system and will be used to make usage decisions pertaining to the energy consumption in real time.

Time series data of the extracted features will be modeled with forecasting methodologies to make future decisions regarding the optimal usage of different apparatus in order to yield enhanced energy efficiency across the nursing home. This inference framework is developed for classification and regression of the metrics data to moderate the prognostic and energy usage predictions in line with posterior distributions that will assign overly high confidence to the estimated class memberships of the feature patterns. Forecasting models for energy usage is also developed for prediction of multivariate time series data with strong correlations and periodic systematic patterns. The prognostic accuracy is estimated using both simulated from experimental test data and known abrupt increase in power usage as well as actual field data read from meter. Features of scientific and practical interest include the presence of sudden changes in usage pattern and intermittent wastage, highly correlated parameters, and the masking of wastage due to the large multivariate and multidimensional characteristics of the data. The tree model shown in Fig. 5 is computationally feasible to include capable of including many possible trees based on critical variables as well as to provide better prediction accuracy to detect and reduce power wastage. This data-driven tree-based approach is utilized as a mechanism for feature selection, failure mode discrimination, and fitting predictive power usage models for self-cognizant prognostics.

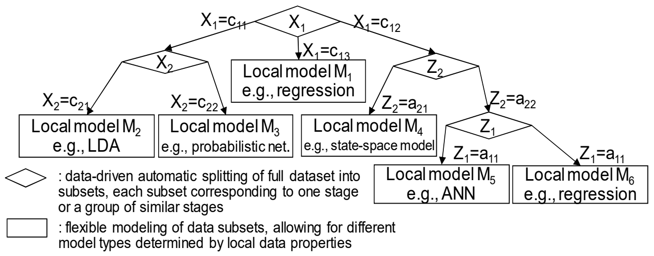

Fig. 5 Data-driven tree-based automatic power wastage modeling strategy

One of the important areas of energy efficiency optimization is a wireless sensing network (WSN) that carries out environmental monitoring. Both wireless sensors that serve varying functions from simple ambient temperature, air quality, to more sophisticated patient tracking for lighting control are coupled with fixed smart meters to fuse data for prognostics. The network is designed from our earlier work in [39] with the Reed-Solomon based coding scheme developed in [40]. To optimize its efficiency, a wake-up sequence is sent to evaluate the minimum power P_{min} for establishing connection. Its sensitivity P_s is:

$$P_s = P_m (1 - R^2) \tag{10}$$

Where R is the voltage reflection coefficient, such that the sensitivity is derived from features detected from the function of the resistance over power [41]. Calibration is referenced with the Short Open and Load (SO) standard [42]. As communication commences, the resistance drops substantially at the power level. The output power P_{out} that measures the chip impedance's real and imaginary parts having a 0.01 dBm step size is plotted in Fig 6, a power sweep in the range of -20 to 10 dBm indicates that it would require a matching network with a reactance of 40 Ω in order to compensate for the capacitance of the RFID chip. Finally, the average power saving is plotted in Fig. 7 over the three-month trial period that yields approximately 10% of power consumption reduction.

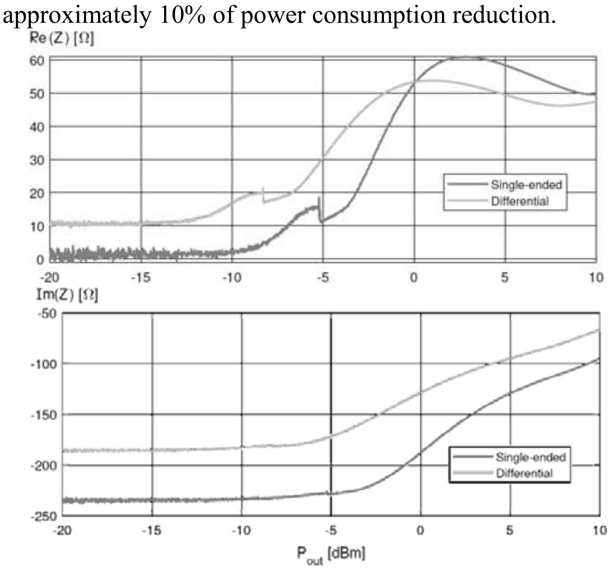

Fig. 6 Measured impedance of the RFID chip as a function of P_{out}

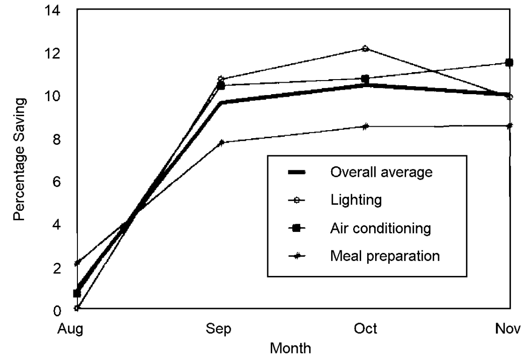

Fig. 7 Average power saving as observed in consumption meter

V. Conclusions

The scope of optimizing power utilization efficiency is becoming an increasingly important topic given the fact that scarcity of energy is an important part of sustainable smart city development. Moreover, the cost of energy resources has risen very substantially since the beginning of year 2022, such that business operators have all the incentives to increase energy efficiency in their premises. Our work presents a self-cognizant prognostics approach that has yielded an average of approximately 10% saving in power consumption for a smart nursing home. We have presented a power monitoring and management system to dynamically adjust relevant parameters to save power without compromising on nursing home residents' health and safety. This would result in considerable cost savings for nursing home operators.

The utilization of self-cognizant prognostics can have a potential of standardizing the way of enhancing energy efficiency in various types of buildings across a smart city. The design and implementation for autonomous commercial power monitoring and management systems will be increasingly important when buildings get smarter and that such system will be integrated into different parts of a business. In our particular case study, we have investigated the effectiveness of the system in three separate areas within a nursing home that are known to be consume a substantial amount of energy, namely lighting, air conditioning and air quality regulation, as well as for meal preparation, with the latter resulting in a somewhat less substantial improvement in power efficiency. The findings in our work show that the development smart power monitoring and management systems are still at a fairly early phase with a three-month trial, yet the improvement in power utilization efficiency yielded is set to improve the way smart buildings can be made more energy efficient in the foreseeable future.

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