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Machine Learning-Based Energy-Saving Framework for Environmental States-Adaptive Wireless Sensor Network

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ABSTRACT In this paper, we propose an energy-saving framework for Wireless Sensor Networks (WSN) using machine learning techniques and meta-heuristics according to environmental states. Unlike conventional topology-based energy-saving methods, we focus on the energy savings of the sensor node in the WSN itself. We attempt two-phase energy savings on the sensor nodes. First, network-level energy saving, called N1-energy saving, is achieved by finding the minimum sensor nodes needed to ensure the performance of the WSN. To find the minimum sensor nodes, we apply hybrid filter-wrapper feature selection, a typical machine learning method, to find the best feature subsets. Second, we achieve energy savings of the WSNs by manipulating the sampling rate and the transmission interval of the sensor nodes to achieve node-level energy saving, which is referred to as N2-energy saving. To do so, we propose an optimization method based on Simulated Annealing (SA), which is an efficient method that can find the approximate global optimum in datasets where it is difficult to collect precise values due to noise problems, such as sensor data. Some numerical examples are shown with respect to several control parameters. We conduct several experiments with real-world sensor data in a smart home to prove the superiority of the proposed method. Through these experiments, the sensor nodes are shown to be selected by a method performing N1-energy savings effectively while minimizing the loss of performance compared to the original WSN. In addition, we demonstrate that N2-energy savings can be achieved while maintaining the QoS of the WSN through an optimal sampling rate and transmission interval determined by the SA.

INDEX TERMS Wireless sensor network, energy-saving, machine learning, hybrid filter-wrapper method

I. INTRODUCTION

The explosive growth of services using Wireless Sensor Networks (WSN) has led to an exponential increase in the number of sensor nodes powered by non-rechargeable batteries with limited capacity. So, energy savings of the sensor nodes and the WSN itself is one of the main challenges to sustain WSNs [1]. To implement energy-efficient WSNs, researchers have developed optimal routing protocols [2], [3], detected faults of the nodes [4], or constructed the topology of WSNs [5]. Some also save energy by manipulating the sampling rate of each sensor node [6]. These methods manipulate the sampling rates by using mathematical optimization models or heuristic models for topology control [5], coverage preservation [7] or localization [8], [9]. However, such model-based WSN management has some limitations as follows. The model-based WSN topology is constructed using predefined functional specifications of the sensor nodes. However, the performance of the sensor nodes, which are deployed in the real-world, greatly depends on the environment in which they operate (e.g., weather, time, location, etc.), and the environment directly affects the quality of the collected sensor data [10]. For example, a light sensor or an image sensor shows a higher resolution and precision during the day than at night. A sound sensor varies in performance depending on the degree of the surrounding sound noise. Nevertheless, a WSN topology configured without considering these environmental states may result in unnecessary energy consumption. In addition, due to the exponential increase in the number of sensor nodes and the emergence of high-performance sensors [11], it is difficult to expect dramatic energy-savings simply by reconfiguring the topology of the WSN without considering the energy consumption of the sensor node itself.

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In order to solve such problems, this paper proposes a new method that significantly reduces energy consumption in WSNs by implementing a combination of machine learning techniques and meta-heuristics. The proposed method executes the energy-savings in two phases. In the first phase, it tries to achieve network-level energy-savings, called N1-energy saving. To do so, the proposed method determines the best subset of the sensor nodes depending on the environmental states in which they operate to configure the WSN topology. In the second phase, it tries to achieve additional energy savings by adjusting the sampling rate and transmission interval of the sensor nodes constituting the WSN (which hereafter we refer to as N2-energy saving).

In the N1-energy savings phase, it is essential to select the minimum subset of sensors from the original sensor set depending on the environmental states. To do so, we propose a sensor selection method based on hybrid filter-wrapper methods in feature selection [12]. To recognize the patterns of data that occur in specific environmental states, the proposed method selects the necessary sensor nodes using information theory and classifier predictive performance. The proposed method seems similar to selective sensing, which turns on only the sensors needed in certain environmental states [13]. However, the proposed method differs from conventional methods when selecting sensor nodes based on the predictive performance of the classifiers. It can minimize the loss of information in the sensor data needed to discriminate patterns, and it further allows for a trade-off between the information loss and the energy savings.

To achieve N1-energy savings, it is necessary to determine the optimal sampling rate and the transmission interval of the sensor nodes considering the operating environments and the quality of service (QoS) of the WSN. Intuitively, energy-efficiency can be achieved by configuring low sampling rates and long transmission intervals. However, it may result in a deterioration of the QoS using WSNs due to communication delays between the sensor nodes and the lack of the sensor data. In this light, for N2-energy savings, the sampling rate and transmission interval must be adjusted considering the between energy-efficiency and the QoS. To do so, we propose an optimal sampling rate and a transmission intervals adjustment method that combines Simulated Annealing (SA) with supervised learning. To do this, we define the objective function of the SA considering the energy consumption of the WSNs and we identify additional constraints to preserve the information of the sensor data for QoS of the WSN using machine learning techniques.

The contributions of this paper can be summarized as follows. First, we consider the environmental states when selecting the sensor subset to reflect the performance of the sensors that change with the environment. In previous work [14], we proposed a method to select the sensor subset and manipulate the sampling rate and the transmission interval for them. However, the method does not account for the environmental states of the sensor nodes, which significantly affect the quality of the sensor data. Therefore, it may result in an infeasible solution for real-world applications. To overcome this problem, we propose a Fuzzy c-means (FCM) clustering-based data sharding method that can make an adaptive framework according to changes in the environmental states. In addition, the wrapper method has been adopted to select the best sensor subset. It may cause excessive computational costs for many sensor nodes in the WSN. We propose an advanced sensor subset selection method by using a hybrid filter-wrapper feature selection method. The new filter measure is proposed using the distances between the sensor nodes, not information theory, and a sensor nodes batching method is developed to reduce the exhaustive wrapper evaluations. Second, we proposed a novel framework to reduce the energy consumption using N1-energy savings and N2-energy savings. Through these two phases of energy savings, we can achieve drastic energy savings in the WSN.

This paper is organized as follows. In Section 2, we review the related research. Section 3 offers the overall framework and detailed process. In Section 4, the experimental results are suggested to demonstrate the effectiveness of the framework. Finally, Section 5 presents the conclusions and further research.

II. RELATED WORK

Energy consumption is one of the main constraints currently affecting WSNs, so many studies have been carried out on energy-awareness routing. First, some researchers attempted to design a routing protocol [16]–[19]. The routing protocol finds the best energy efficient paths from the source node to the destination node in the WSN [15]. Brar *et al.* [16] proposed energy an efficient direction transmission-based energy aware routing protocol called PDORP, which is developed through a hybridization of genetic algorithms and bacterial foraging optimization. It shows a high throughput, reduced delay, and less energy consumption in the WSN. Haseeb *et al.* [17] proposed secret sharing to resolve the high energy consumption problem of a multi-hop routing protocol. Xu *at al.* [18] proposed a source routing-based energy-efficient region routing protocol called ER-SR, which reduces the energy consumption of the data transmission and balances the energy consumption among different nodes jointly. Furthermore, to minimize the energy consumption, they introduced a distance-based ant colony algorithm to find the optimal transmission path. Zhang *et al.* [19] proposed E-BEENISH, a balanced energy efficient network, by integrating super-heterogeneous processing and a routing protocol. E-BEENISH uses single-hop communication for heterogeneous WSNs. It is based on the weighted election probabilities of each node to overcome heterogeneity between them.

There is another way to reduce the energy consumption, the topology control of the WSN. The topology control algorithm is divided into two different problems: topology construction and topology maintenance. The topology construction builds an energy efficient topology of the WSN [20]. Saha and McLauchlan [21] proposed an energy-aware topology construction protocol named EAST. EAST builds on the minimal spanning tree method. This protocol places weaker (or unconnected) nodes into a sleep mode while maintaining connectivity and coverage of the network. Gong *et al.* [22] proposed a distributed algorithm called toward source tree (TST), which builds approximate minimum-length multicast trees in WSNs to improve the efficiency of the data dissemination. Yu *et al.* [23] proposed a cluster tree topology construction method based on particle swarm optimization (PSO) for WSNs. They use the PSO to solve optimization problems by constructing an evaluation function that reflects the energy consumption. All of these topology construction methods can reduce the energy consumption and can consequently prolong the lifetime of the WSNs. The topology maintenance is an iterative process of constructing, restoring and switching to obtain the best topology according to changes in the WSN. Rajeswari and Seenivasagam [24] proposed a topology maintenance protocol that conserves energy. The proposed protocol considers the location information, sleep cycle scheduling, and locomotion control to improve the lifetime of the networks. In particular, the sleep cycle is scheduled to reduce the energy consumption.

In recent, many researchers have exploited optimization algorithms for routing protocols and topology control, and some research that uses machine learning techniques has also been proposed. Alsheikh *et al.* [25] indicated that machine learning techniques can be a practical solution to improve energy efficiency. These can also overcome the unexpected environmental behaviors or circumstances. Barnawi and Keshta [26] compared energy management models using Naïve Bayes, MLP and Linear-SVM. In this paper, the energy management the model based on Linear-SVM shows the best energy efficiency compared to others. Also, some research attempts to adopt reinforcement learning techniques to optimize the routing protocol of the WSN instead of the meta-heuristics. Oddi *et al.* [27] proposed a routing algorithm to prolong the network lifetime by balancing the routing effort among sensor nodes based on reinforcement learning. Kiani *et al.* [28] also applied reinforcement learning to make intelligent routing protocol systems. At this time, the appropriate data transmission time determines the Q-value parameter of the reinforcement learning.

III. PROPOSED ARCHITECTURE FOR THE ENERGY SAVINGS OF WSNS

The architecture of the energy savings for the WSNs consists of three modules, including the Environmental States Discovery Module (ESDM), Environmental state-adaptive Sensor Selection Module (ESSM), and Optimal Schedule Determination Module (OSDM). The schematic depicted in Figure 1 shows the architecture for the WSN energy savings.

The ESDM performs data preprocessing for data sharding (or horizontal partitioning). At this time, the criteria of the data sharding are environmental states, which are Spatio-temporal conditions that can affect the performance of the

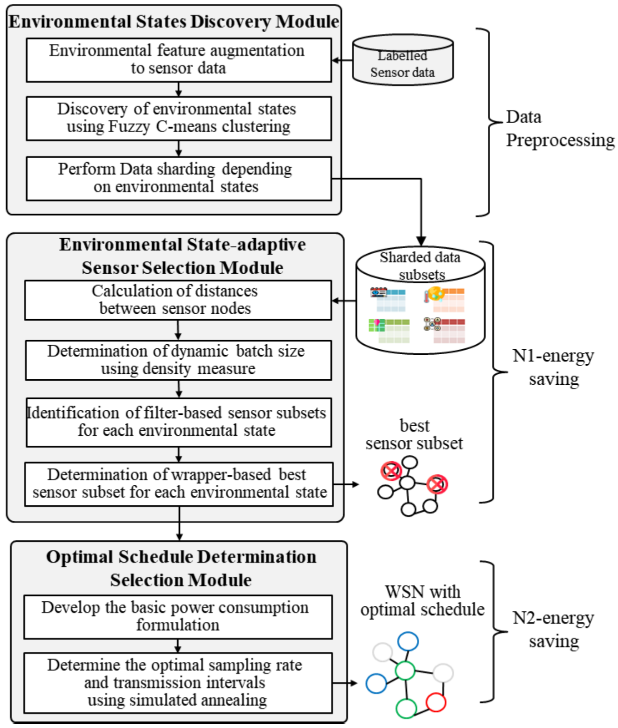

FIGURE 1. Schematic architecture of energy savings of the WSN.

sensor nodes when the WSNs are working to provide services.

The ESSM is conducted to achieve N1-energy savings. To do so, it searches for all sensor nodes in the WSN to determine the sensor subsets that are as small as possible. As a method to determine the sensor subsets, we propose a hybrid filter-wrapper sensor selection technique that can find batches of sensors to be evaluated.

The OSDM determines the optimal sampling rate and the transmission interval of the selected sensors depending on the environmental states in order to achieve N2-energy savings. To do so, the OSDM solves the optimization problem with the objective function taking into account the energy consumption of the sensor node itself and the constraints necessary to preserve the performance of the WSN.

A. ENVIRONMENTAL STATES DISCOVERY MODULE

To achieve energy savings with the proposed method, the environmental states in which the WSN works must be clearly distinguished. Prior to describing how to determine the environmental states, we define the variables required for these.

Definition 1: Labeled sensor dataset (*SD*) is a matrix as follows.

$$\mathrm{SD} = (S_1 \ldots S_i \ldots S_m T) \tag{1}$$

where S_i is a $N \times n_i$ sub-matrix to represent the sensor data collected subset from the i^{th} sensor, N is the total number of sensor data samples, and n_i is the total number of the feature of i^{th} sensor. In addition, S_i is composed of feature vectors

F_{ik} $(k = 1, 2, \ldots, n_i)$ and has at least three features for time, location, and sensor data $(n_i \geq 3)$. T is a vector of the target label, which is a class for a specific sensor data, t has one of the classes included in class set C as a label.

However, it is difficult to determine the exact environmental states in which the data was collected by the *SD* alone, which includes only the time and location of the data collection. To solve the problem, we augment the temporal features and spatial features to *SD* that have the biggest impact on the performance of the WSN sensor nodes. As a result, an augmented labeled sensor dataset (*ASD*) is generated. At this time, the temporal features and spatial features of the ASD are discretized into day, night, weekday, weekend, home, office, park, etc. The ASD is represented as follows.

Definition 2: Augmented labeled sensor dataset (ASD) is a matrix as follows.

$$\mathrm{ASD} = (S_1 \ldots S_i \ldots S_m \ldots A_l^t \ldots A_o^s \ldots T) \tag{2}$$

where A_l^t and A_o^s are composed of feature vectors, which represent temporal features and spatial features, respectively $(1 \leq l, o, m < l < o)$.

However, augmented sensor data occurs in different environmental states. Thus, the patterns of the environmental states can be generated for as many as the number of sensor data. Due to the high variability in the patterns of the environmental state, this can result in a heavy computational cost and risks the loss of accuracy in order to find the sensor subset. To reduce this cost and risk, Fuzzy C-means (FCM) clustering is used to bring together environmental states among similar ones. FCM clustering is the best choice for the hard boundary problems where it is difficult to clearly distinguish one sensor data into an environmental state like ASD. Furthermore, by applying the membership function to the distance measure of the clustering method, FCM clustering shows good performance when the cluster overlaps [29]. The distance function between the centroid and the data needed to perform FCM clustering is calculated as follows.

$$d\left(x_n, ct_c\right) = \|x_n - ct_c\|^p \tag{3}$$

where $\boldsymbol{x}_n$ is n$^{\text{th}}$ sample of sensor data in *ASD*, ct_c is randomly selected data sample as a centroid $(ct_c \subset \mathrm{ASD}, c \leq C)$, C is the number of clusters, and p is the distance order, such as Manhattan $(p = 1)$ and Euclidean $(p = 2)$.

In addition, if two arbitrary clusters in ASD are overlap, the cost function to distinguish them is as follows.

$$\text{cost function} = \sum_{\mathrm{c}=1}^{C} \sum_{\mathrm{n}=1}^{N} w_{nc}^m d\left(x_n, ct_c\right) \tag{4}$$

where w_{nc}^m is the membership value for which $\boldsymbol{x}_n$ belongs to the c^{th} cluster, and m is a parameter to determine the level of cluster fuzziness. The Lagrangian multiplier is applied to find the optimal ct_c and w_{nc}^m to minimize the cost function. The Lagrangian multiplier is applied as follows [30].

$$\begin{cases} ct_c = \dfrac{\sum_{n=1}^{N} w_{nc}^m x_i}{\sum_{n=1}^{N} w_{nc}^m}, \quad c = 1, \ldots, C \\ w_{nc} = \dfrac{\left(\frac{1}{d(x_n, ct_c)}\right)^{\frac{2}{m-1}}}{\sum_{t=1}^{C}\left(\dfrac{1}{d\left(x_n, ct_t\right)}\right)^{\frac{2}{m-1}}} \end{cases} \tag{5}$$

The cost function is updated using the optimal ct_c and w_{nc}^m. This process is repeated until the centroid ct_c converges to a specific value. As a result, FCM clustering determines the following environmental states ES_c. At this time, one c^{th} cluster is mapped to one ES_c.

Definition 3: c^{th} environmental state (ES_c) is a set of feature intervals of ASD to describe an environmental state. It is represented as follows.

$$ES_c = \{\ldots R_{ik} \ldots\} \tag{6}$$

where R_{ik} is a range $\left[r_{ik}^-, r_{ik}^+\right]$ of F_{ik}, r_{ik}^- and r_{ik}^+ are minimum and maximum value in c^{th} cluster, respectively.

The overall procedure of the FCM clustering for environmental states discovery is summarized in Algorithm 1.

Finally, a data sharding for SD is conducted using ES_c. As a result, shared sensor dataset (sSD_c) depending on the environmental state is generated as follows.

Definition 4: The shared sensor dataset considering the environmental state (sSD_c) is represented by the following matrix.

$$sSD_c = (sS_1 \ldots sS_i \ldots sS_m T) \tag{7}$$

where sS_i is a sharded data subset $(sS_i \subset S_i)$, and all samples $x_n \in sS_i$ satisfy R_{ik} for all k.

sSD_c is used for N- saving and N2-energy saving depending on the environmental states.

B. ENVIRONMENTAL STATE-ADAPTIVE SENSOR SELECTION MODULE

The ESSM determines the sensor subsets from sSD_c which each target label can be classified as the most efficient in terms of energy. As shown in Table 1, the structure is very similar to the problem of finding a subset of energy-efficient sensors in the WSN with many sensor nodes and the selection of a subset of features needed to classify the classes from a high-dimensional dataset with many features as well.

Thus, we will determine the environmental state-adaptive sensor subsets using a hybrid filter-wrapper method [12], which is known as the most efficient way to find feature subsets. However, even if a hybrid method with low computational complexity is used, it results in a high time complexity and computational burden to find the subsets of the sensor nodes for WSNs that contain a large number of sensor nodes. In addition, the burden is exacerbated because we must also consider the environmental states.

To reduce this burden, we devise a novel filter method, not the variance or information theory, but one that can reflect the

TABLE 1. Comparison of feature selection and sensor subsets selection.

	Feature selection	Sensor subsets selection
Objective	Small informative feature subset	Small energy efficient sensor subsets
Domain	Data mining	WSN
Targets	Features	Sensor nodes
Selection criteria	Predictive performance	Predictive performance and energy efficiency
Results	Feature subset	Sensor nodes subset

distance between the sensor nodes. To mitigate the burden of the wrapper method due to exhaustive evaluations, we only perform evaluation on batches of adjacent sensor nodes, not all possible subsets of the sensor nodes. To do so, we first have to find the batches, which are composed of adjacent sensor nodes in the WSN. At this time, the batches are found by the distance between the sensor nodes and the density of the sensor nodes. The distance between two arbitrary sensor nodes ($a, b \in i, a \neq b$) in the WSN is calculated as follows.

$$d_{ab} = \left|\mu_a^{lo} - \mu_b^{lo}\right| / (max\left(\mu_i^{lo}\right) - min\left(\mu_i^{lo}\right)) \tag{8}$$

where μ_i^{lo} is a mean value for all location data of S_i

For each pair of sensor nodes in the WSN, the distance is calculated using equation (8). As a result, the m $\times$ m distance matrix D is generated as follows.

Definition 5 (Distance Matrix): (D) is a symmetrical distance matrix between sensor nodes in the WSN.

$$D = [\ldots d_{ab} \ldots] \tag{9}$$

where d_{ab} is the distance between two sensor nodes a, b by (8), and $d_{ab} = d_{ba}$.

Using this matrix D, batch B_i based on an arbitrary sensor node S_i is added gradually from the sensor closest to S_i. Also, all batches are disjoint for each other and do not have the same sensor ($B_i \cup B_{i'} = \phi$). In general, the size of batches ($|B_i|$), i.e, the number of sensor nodes to be included in the batches, is a constant determined using an empirical study. However, it is hard to find a best $|B_i|$ to deal with lots of sensor nodes, since the vastness of the WSN needs dynamic $|B_i|$ to compose the close sensor nodes as elements of B_i according to the deployment pattern around S_i. To do this, we propose a method to dynamically determine the size of the batches ($|B_i|$) using the density. It is the number of sensors located at a radius rd about an arbitrary sensor S_i as depicted in Figure 2-(a). The density is calculated as follows.

$$density\,(S_i, rd) = \left|\left\{S_{i'} | d_{ii'} \leq rd, i \neq i''\right\}\right| \tag{10}$$

where rd is a constant value to represent the radius of S_i.

To determine $|B_i|$, we perform a polynomial regression on the density, $density\,(S_i, rd)$, and find the pole using the derivative. In general, polynomial regression is calculated using the Lagrange method. However, if the number of data points (at this time, the number of sensor nodes) is not accurately known, a non-decreasing characteristic cannot be reflected

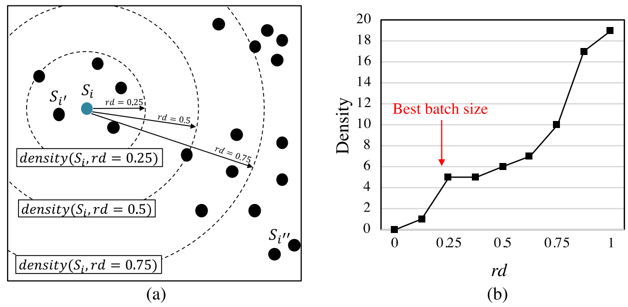

FIGURE 2. (a) Sensor nods deployment and (b) density plotting of i^{th} sensor node according to the radius.

due to the degree of the estimated polynomial equation. To avoid this problem, we performed an estimation using a 3rd degree polynomial equation to find the poles clearly. For a given condition, the polynomial regression y based on the 3rd degree polynomial equation is as follows.

$$\mathrm{y} = a_0 + a_1 x + a_2 x^2 + a_3 x^3 \quad s.t\,(a_2)^2 - 3a_1 a_3 > 0 \tag{11}$$

For all B_i, we apply the wrapper method to determine the minimum sensor subset sS_i^* to classify the target label (T) with a high accuracy rate ($\sum_{i=1} \left|sS_i^*\right| \leq m$). The wrapper method performs learning for any classifier using all possible sensor subsets and target label (T). Then it selects the sensor subset that has the best classification results in terms of accuracy, recall, and F1 measurements. At this time, the results of the wrapper method vary depending on which performance measure is to be applied. In general, the most widely used performance measure is the accuracy to obtain a high accuracy rate for only T. If an unexpected pattern not included in T occurs, selecting the sensor subset by accuracy is infeasible. Thus, we choose the recall measure to guarantee the stability of the sensor data for unexpected patterns not included in T. In addition, by considering the additional energy consumption, the wrapper selects the sensor subsets with stable and low energy consumption as sS_i^*. The performance score of the wrapper using recall and energy consumption is calculated as follows.

$$\mathrm{EAS_i} = \mathrm{Recall} - ec_i/2(ec_{max} - ec_{min}) \tag{12}$$

where ec_i is the energy consumption of the ith sensor. ec_{max} and ec_{min} are maximum and minimum energy consumption among the sensors, respectively.

Algorithm 2 describes the process of selecting the best sensor subset from sSD_c using the dynamic batch.

After all, we can achieve N1-energy savings by using only the smallest sensor subset (sSD_c^*) that has a high performance ($sSD_c^* = (\ldots sS_{i^*} \ldots T)$).

C. OPTIMAL SCHEDULE DETERMINATION MODULE

In the previous module, we determine the best sensor subset sSD_c^* according to an environmental state, which can contribute N1-energy savings of the WSN. Using the best sensor subsets, we attempted to determine the sampling rate and the transmission interval of the sensors that can maintain the performance of the WSN while achieving energy savings. To do so, we propose an optimization method based on Simulated Annealing (SA), which is an efficient method to find approximate global optimum in datasets where it is difficult to collect precise values due to noise problems, such as sensor data [31].

The basic power consumption of the sSD_c^* (P_c) is simply represented as follows.

$$P_c = \sum_{i}^{*} \left(\frac{Ce_{i^*}}{\alpha_{i^*}} + \beta_{i^*} Te_{i^*}\right) \tag{13}$$

where α_{i^*} is the sampling rate of sS_{i^*}, C_{i^*} is the energy consumption per sampling, β_{i^*} is the transmission interval, and Te_i is the energy consumption per transmission.

According to Equation (13), since the power consumption P_c is a linear function, it is most commonly used to decrease $\alpha_{\mathrm{i^*,epoch}}$ and increase $\beta_{\mathrm{i^*,epoch}}$ to minimize the power consumption. However, if we set $\alpha_{\mathrm{i^*,epoch}}$ and increase $\beta_{\mathrm{i^*,epoch}}$ in this way, the performance of the WSN (e.g. QoS) can be significantly degraded. To prevent the degradation of the WSN performance, we propose a revised objective (loss) function and basic constraint as follows.

$$\begin{aligned} &min\ L_{ep} = min \sum_{i*} \left(\frac{Ce_{i^*}}{\alpha_{i^*,ep}} + \beta_{i^*,ep} Te_{i^*}\right) + Recall_{ep} \\ &s.t.\ \Pr\left(e, e', Tp\right) > random(0, 1) \end{aligned} \tag{14}$$

where $\mathrm{e} = \mathrm{P_c}\left(\alpha_{\mathrm{i^*,ep}}, \beta_{\mathrm{i^*,ep}}\right)$, $\mathrm{e}' = \mathrm{P_c}(\alpha'_{\mathrm{i^*,ep}}, \beta'_{\mathrm{i^*,ep}})$, $\Pr\left(\mathrm{e}, \mathrm{e}', \mathrm{Tp}\right) = e^{-\left(\mathrm{P_c'} - \mathrm{P_c}\right)/\mathrm{Tp}}$, $\mathrm{A}'_{\mathrm{i^*,ep}}$, and $\beta'_{\mathrm{i^*,ep}}$ are the neighborhood of $\alpha_{\mathrm{i^*,ep}}$ and $\beta_{\mathrm{i^*,ep}}$, respectively, Tp is a temperature of SA, L_{ep} is loss in current epoch.

Furthermore, it needs an additional constraint that can prevent the transmission of sensor data before it is sufficiently collected. This constraint prevents performance degradation of the WSN by preventing missing value operations in the cloud. The constraint is as follows.

$$\gamma \times min\left(\frac{1}{\alpha_{i^*}}\right) < min\max\left(\beta_{i^*}\right), \quad \forall i^* \tag{15}$$

where γ is the number of sensor data points to be transmitted.

The proposed method achieves N1-energy saving by reducing the number of sensor nodes in the WSN. So, it can result in performance degradation compared to traditional methods using all sensor nodes in the WSN. In order to prevent dramatic degradation of the WSN performance, we added the following constraints:

$$\begin{aligned} \mathrm{Acc_{ep}} &\geq \theta_{\mathrm{acc}} \times \kappa \\ Rec_{\mathrm{ep}} &\geq \theta_{\mathrm{rec}} \times \kappa \end{aligned} \tag{16}$$

where κ is a constant to determine the allowed loss of predictive performance for θ_{acc} and θ_{rec} ($0 < \kappa < 1$). θ_{acc} and θ_{rec} are the accuracy and recall for all sensor nodes in the WSN, respectively. $\mathrm{Acc_{epoch}}$ and Rec_{epoch} are the accuracy and recall in an epoch, respectively.

TABLE 2. The summary of used sensors and sensor data type.

Sensors	Data type	Descriptions
Light	Integer	illuminance
Infrared Motion	Categorical (binary)	movement
Door sensor	Categorical (binary	whether the door is open or closed
Temperature	Float	ambient temperature

TABLE 3. The statistics of the wsn in a smart home.

datasets	No. sensors	No. features	No. class	Sensing time
1	70	223	23	12 days
2	75	242	25	6 days

However, the constraints of the proposed SA method are not as precise as those of the general SA method. As a result, its search space can be large. As a result, the convergence speed to the optimum value may slow due to a decrease in the temperature (Tp). And the sub-optimal may be encountered despite enough repetition. To resolve these problems, we use additional constraint that adds momentum η to conventional temperature reduction conditions. The constraint is as follows.

$$\begin{aligned} &Drop\ condition: \frac{T_{max}}{(T + 1 + \eta)} \\ &\text{where } \eta = \begin{cases} 1 & (L_{ep} > L_{ep+1}) \\ 0 & (otherwise) \end{cases} \end{aligned} \tag{17}$$

Using the basic power consumption and additional constrains, we determine the optimal sample rate and transmission interval for the sensor nodes included in sSD_c^* for all c.

IV. EXPERIMENTS AND PERFORMANCE EVALUATION

To prove the superiority of the proposed framework, we design several experiments using the 2 CASAS smart hone sensor datasets collected from the WSN single resident apartments [32]. These sensor datasets include sensor data for various sensors installed at home and activity labels such as sleep, dress, phone, grooming and so on. The types of sensor nodes are the same for all datasets, and Table 2 provides a summary of the sensors and sensor data type. Each of the smart homes has rooms for bed, dining, kitchen, and living at least. Although the types of sensor nodes are the same, the WSN of the datasets are different in the number of sensor nodes, deployment, internal structure of home, and so on. The statistics of the WSN are explained in Table 3.

Using the CASAS datasets, we perform the experiments to prove the performance of the proposed filter-wrapper method and the optimal sampling rate and transmission interval method.

A. THE PERFORMANCE OF THE FILTER-WRAPPER SENSOR SELECTION IN A SMART HOME

The CASAS sensor nodes are installed to detect and sense activity at home. However, there are many sensor nodes

TABLE 4. The predictive performance for the size of selected sensor.

	The size of selected sensor subset									
measures	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
acc-1	0.88380	0.90305	0.90289	0.90413	0.89519	0.90355	0.89436	0.90281	0.89221	0.90239
acc-2	0.71948	0.74604	0.76389	0.76769	0.77215	0.77617	0.77126	0.77460	0.76813	0.77304
rec-1	0.44610	0.49027	0.49450	0.49469	0.48822	0.49241	0.48167	0.49000	0.46246	0.48979
rec-2	0.46023	0.53776	0.54708	0.54892	0.54894	0.54820	0.54241	0.54042	0.53732	0.54703
F1-1	0.47280	0.51502	0.52205	0.52130	0.52061	0.52071	0.51397	0.52004	0.49169	0.52065
F1-2	0.45919	0.54601	0.55657	0.55982	0.56553	0.56160	0.55443	0.54872	0.55927	0.56446

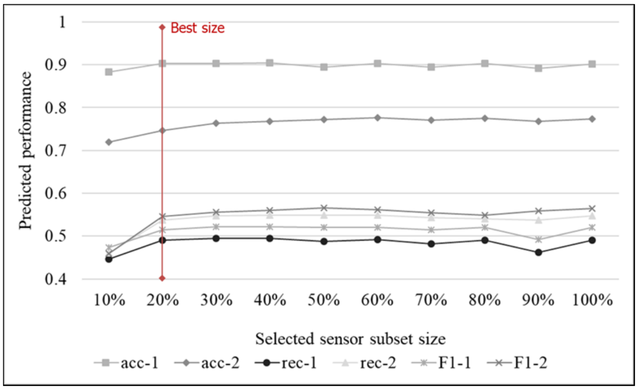

FIGURE 3. Predictive performance of the size of selected sensor subset.

even in a room, and this leads to redundant or unnecessary sensors to detect activities. We conduct the proposed the filter-wrapper sensor selection and compare the predictive performance of the selected sensor subset and all sensor sets. Furthermore, we compare the number of wrapper evaluations using a batching method and all possible subsets as a target set to be evaluated. It will prove the high speed and low computational complexity of our batch method. First, Table 4 describes the overall results of the accuracy (acc), recall (rec), and F1-measure (F1) for two datasets (1,2) according to changes of the selected sensor subset size. The predictive performance for all sizes of selected sensor subsets is shown in Figure 3.

The results of this experiment show that most of the measures do not produce significant performance differences from 20% onwards. In other words, the predictive performance is similar when using original WSN and using only 20% of its sensor subset. Rather, when the size of the sensor subset is 90%, most measures are not good. The reason is that inappropriate sensor nodes can make noise that disturbs the classification of patterns. Thus, using more sensors does not always have a good effect on the predictive performance. Based on these results, our sensor selection method can achieve N2-energy savings with the use of significantly less sensors while maintaining sufficient predictive performance of the original WSN. Moreover, the optimal sensor configuration and number of sensors to maximize the predictive performance of the WSN can be additionally known.

B. THE RESULTS OF OPTIMAL SAMPLING RATE AND TRANSMISSION INTERVAL BY ENERGY-AWARE AND MACHINE LEARNING-BASED SA

The proposed framework finds and determines the optimal sampling rate and transmission interval using modified SA. To prove the N1-energy savings performance of the proposed method, we describe the area to be searched for by the SA using possible sampling rates and transmission intervals with the previous best 20% of the sensor subsets and analyze the location of the optimum we found. The results are shown in Figure 4, where each area is for datasets 1, 2. To equalize the measure of the x-axis and y-axis, we used 1/sampling rate instead of the sampling rate.

As Figure 4 shows, the loss increases with a higher sampling rate, and the loss decreases with a long transmission interval. This is a natural result. A higher sampling rate derives a higher loss with the small sensor data set. Similarly, the long transmission intervals increase the delay of the sensor data to be transmitted, and this leads to loss due to the lack of information to classify patterns. However, this loss stabilizes quickly and a sensor node with too low a sampling rate and short transmission interval cannot help improve the accuracy. Rather, it results in unnecessary energy consumption. Therefore, finding the most optimal sampling rate and transmission intervals in this trade-off relationship is very important and can drastically reduce the sensor node energy.

Looking at the solution found in our method, we can find a sampling rate and transmission close to the optimum. Although the default values of 1/sampling rate and transmission rate were 0.05 seconds, our method suggested more than 10 times bigger than the values. Also, the performances of the WSNs are similar with the best accuracy. This means our method can reduce the energy consumption by more than 90%.

However, a balance between the sampling rate and the transmission was not clearly found. The solution from dataset 1 yielded better results for the sampling rate, while the solution for dataset 2 yielded better results for the transmission intervals. Also, we did not choose the sampling rate and transmission interval very tightly because we chose recall rather than acc to find a solution based on the stability of the sensor data. Given this, our method found a good solution for

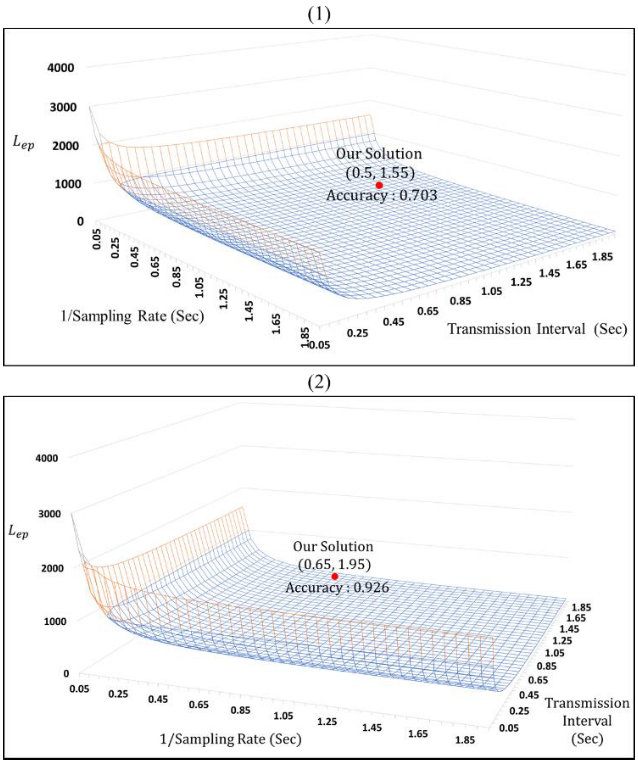

FIGURE 4. Search space and our solution using SA according to sample rates and transmission intervals.

both datasets, preventing unnecessary energy consumption of the sensor nodes.

V. CONCLUSION AND FUTURE WORKS

We proposed energy savings for the WSN framework using machine learning techniques and meta-heuristics considering the environmental states. Furthermore, we proved superiority of the proposed framework using several experiments. Unlike traditional energy-savings approaches to change the structure of the WSN in terms of the topology, we have achieved energy savings by directly reducing the sensor nodes or adjusting their sampling rate and transmission interval in the WSN. In addition, we applied machine learning techniques to the meta-heuristics to suggest a new energy savings strategy in terms of the information of the sensor data. The effect on the suggestion can be proved with experiments with CASAS datasets in real-world sensor data, and we confirmed possibilities e that the adjusted WSN obtained with our method can have high QoS on sensor data with less energy consumption.

Despite the superior performance, the proposed method has the following limitations. Since we did not consider the topology of the WSN, our method can be infeasible in the real-world due to bad routing protocols and complex topology. In addition, we tried to reduce the computational complexity of our proposed method and achieved a reduction of it, but the proposed method still has a lack of scalability to handle changes in the WSN. Finally, the proposed method cannot be applied to a WSN without labeled sensor data, since it utilizes supervised learning techniques.

In future works, we will improve the method to overcome limitations that have been identified. Network or graph theory can be adopted to consider the topology of the WSNs, or the topological features may be good information to select the best sensor subset to preserve an efficient structure of the WSNs. Furthermore, we consider the boosting algorithm of the feature selection to obtain scalability of our method. We will devise a method to take advantage of unsupervised learning techniques so that our method can be applied in the WSNs without labeled sensor data. Finally, to reduce the dependency on the sensor data, we will study a way to use ontology or linked data to effectively control the sensor or its sampling rate and transmission interval.

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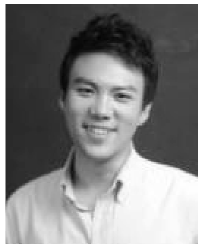

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