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Energy aware measurement scheduling in WSNs used in AAL applications

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Abstract—**In Wireless Sensor Networks (WSNs) developed for Ambient Assisted Living (AAL) applications the supply of the required power is one of the most challenging problems. Batteries have remarkable drawbacks and in some cases, the change of batteries is impossible (space, infected area, etc.). We approached the problem from two directions: 1) The energy for the sensor node's operation should be harvested from the environment and 2) the nodes should work as efficiently as possible. A new method is presented, which optimizes the whole network energy demand while maintaining the performance of the system, with the scheduling of the measurements and sensors. It is taken into account that both the measurement of a physical variable and the transmission of a message have different costs. Selection of sensors and measurement intervals in the system is based on a cost assigned to each sensor, which considers 1) the estimated state of the observed variable based on the past measurements and a model, 2) the actual energy state of the sensor and 3) the possible future events which will affect the energy levels and/or the observed variable. A Hidden Markov Model (HMM) is used to assign probabilities to the states of the unknown variables, which are to be observed. The probabilities of the state transitions are specified by a learning process. Then a defined cost function is applied to calculate the cost of each sensor, the sensors with the minimal cost will be configured for more frequent measurements ensuring the precision, and the others will be configured to less frequent measurements to save energy.**

Keywords-wireless sensor network; measurement scheduling; energy harvesting, ambient assisted living

I. INTRODUCTION AND SURVEY

Wireless sensor networks (WSNs) have some or all of the following properties: **1)** wireless, ad hoc communication, **2)** mobility, topology changes, **3)** energy limitations, **4)** spatial distribution of sensors and computational resources [3]. In typical ambient assisted living (AAL) applications the first and second properties are not common because the area is not too large, usually the sensors have fixed locations, therefore a simple fixed star topology could be used. On the other hand the energy limitations cause usually crucial problems. A WSN for AAL application could use batteries for power supply, but the frequent change of them is intolerable in a network which contains 10 or more sensors. Using a different solution the wiring required to power the sensor network from the local power lines is problematic in several such applications.

In the usual AAL scenario the data transfer adds up to the major part of the energy consumption. For this reason the frequency of communication should be minimized; the sensor must initiate the communication and after that it will engage sleep

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mode. It means that the central unit has to decide the sampling interval of the sensors in advance, and must give it during the communication initiated by the sensor.

A. *Survey of the suggested methods*

Many researchers and papers deal with different aspects of wireless sensor networks, but the majority of them are aimed at solving routing or clustering problems and relatively few are engaged in energy management, especially in sensor and measurement scheduling problems. For example according to a current survey paper [3] more than half of the publications reviewed dealt with routing and clustering. Scheduling in WSN's often means the scheduling of the communication packages in the network layer to gain the maximal data throughput. Higher level scheduling means the control of the sensor's sampling rates to ensure effective energy usage.

In order to get an energy efficient WSN, the source of power from battery to more sustainable solutions like energy harvesting (e.g. solar power) [1],[10],[12] should be extended. In [5] an optimal solar-cell based battery charging method is presented, the authors also presented a sensor node design which main purpose is effective power utilization in [7]. Besides the hardware considerations we have to minimize the energy demand in a way that the network's performance must not be affected dramatically. It is straightforward that scheduling the sampling rates of the sensors influences both the achieved measurement precision and the energy consumption of the network (trade-off). In [15] local scheduling methods are presented where the sampling rates of the sensors were adjusted according to the measured signal's estimated frequency, this method is refined in [16] and an algorithm is shown how to adjust the sampling rate. In many cases collaboration of the sensors and global scheduling are required; e.g. [4] shows a data-driven sensor selection method for power optimization based on the actual measurements and the capabilities of a particular sensor. Sensor selection is addressed in [8], a quantitative measure is proposed to represent the actual utility of a sensor based on a Bayesian approach and the selection can be performed according to this measure. Global scheduling of the sensors and measurements can be the most effective in target tracking problems. The authors of [2],[9] proposed to formulate the problem as a partially observable Markov decision process (POMDP), this method is further elaborated in [6]. In [14] the sensor selection and scheduling of a target tracking problem is solved with extended Kalman filter algorithm, in the WSN a second low power radio channel is used for maintaining the sensors timing parameters.

B. *The suggested new method*

In this paper a method is proposed that represents the observed variables as a temporal probability process, which is modeled using the Markov's principle. The actual and predicted future states of both the observed system variables and the environment are estimated as well. The state of the system is important because the relevance of a sensor varies in different states (e.g. no activity is in the room where the sensor is deployed). The state of the environment is important because sustainable operation (energy harvesting) is the goal, and the state of the environment affects the harvestable energy (in solar cell case the illumination level: sunrise or the lighting is on).

Based on these estimations a time and state dependent cost for each sensor is calculated, and the sampling times of the sensors are scheduled according to their costs. It should be mentioned here that the sensor's energy consumption could be data dependent; measured values are transmitted only if there is a change compared to the previous measured ones. Because the final energy consumption is the sum of the energy needed for the measurement and for the transmission; energy consumption becomes data dependent. As mentioned in [9], if the optimal sensor schedule is data dependent, it cannot be determined a priori. In our proposed method the observed system is represented using a Hidden Markov Model (HMM, as suggested in [2], [9]), because some of the variables cannot be measured directly, and the behavior of the system (e.g. the person in a flat) can be described and predicted properly based on the recent events only. The main difference comprises from two aspects compared to all the previous suggestions ([2], [9], [14]):

- The sensors to be used are not selected in each discrete time step; because the active reception mode of the sensors (which mode is needed for this operation) is as costly as data transmission. Therefore a sensor is configured only in the acknowledgement message after its measurement message arrived (see Fig.1). Configuration in that sense is the setting of the sleep time before the next measurement. This could deteriorate the measurement precision in some extent, but due to the fact that the energy consumption is critical this operation is used. The sensor works only from the start of the measurement until the end of the processing of the acknowledge message, in all other time intervals it is in sleep mode.
- Usually more than one sensors are selected at a time. It is caused by two facts: **1)** in different states different sensors give more relevant information about the process; **2)** only a probabilistic estimate for the next state is available. Taking into account that sometimes the selection of the relevant sensors is delayed (because the sensors can be configured using the acknowledgement messages only) the system should prepare itself for different possible states, using different sensors for maintaining the precision.

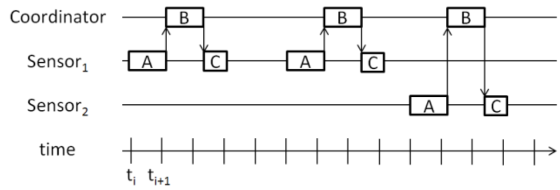

Figure 1. Sequence diagram of the communication between the coordinator and two motion sensors. “A” means: Motion event happened or a scheduled transmission is performed by the sensor. “B” means: Coordinator processes the new data and calculate the next wake-up time for this sensor and send it back in the acknowledgement. “C” means: The sensor processes the acknowledgement and goes into sleep mode for the given time.

The rest of the paper is organized as follows. In the first part some design principles of an energy harvesting wireless sensor node is presented, and in the second part the ideas of the measurement scheduling using HMM representation of the observed variables is presented. In the last part an actual application example will be given and simulation of an energy harvesting WSN for monitoring a person’s motion in an AAL application is shown. Our final goal is to create a WSN containing motion and other simple sensors, which is able to operate battery-less in indoor environments.

II. Hardware Design Considerations

In order to understand self-sustainable operation [12], the following inequality is to be satisfied:

$$E(t) = \int_{t_0}^{t_0+t} P_H(\tau)d\tau - \int_{t_0}^{t_0+t} P_C(\tau)d\tau - \int_{t_0}^{t_0+t} P_L(\tau)d\tau + E(t_0) \tag{1}$$

$$E(t) \geq E_{\min} \text{ for all } t_0 \leq t \leq t_0 + T \tag{2}$$

where t is the current time, t_0 is the starting time of operation, T is the length of the operating interval, $E(t_0)$ is the energy provided at start, $E(t)$ is the current energy available for the sensor, $E_{\min}$ is the minimal energy needed for operation. $P_H(t)$, $P_C(t)$ mean harvested and consumed power respectively; $P_L(t)$ means power loss; which all are continuous and bounded functions of time. The only parameter, which cannot be controlled during the work of the sensor network is $P_{H,available}(t)$ the maximum power, which can be harvested; it is an upper bound of $P_H(t)$. This maximum available power is very time dependent, e.g. it depends heavily on the current illumination, if solar energy is harvested. We only have a priori knowledge and assumptions about it. Based on this information and the experience collected, some predictions could be done about the harvestable power in the near future. The consumed and lost energy can be influenced not only by the design of the sensor node but by properly controlling the sampling time intervals as well. $P_C(t)$ depends on the sensor, and the frequency and duration of active periods, beyond the measurement the frequency of the data transmission is an important factor in it. $P_L(t)$ is mainly generated by the energy storage device, the voltage conversions, and other passive electrical components (mainly by the power management module). In order to satisfy (2) the consumption and loss should be minimized and the harvested energy should be maximized.

Our goal is to create a sensor node, which has remarkable low energy demand, and harvests energy from its environment with good efficiency. In order to achieve this, 3 sub-modules are needed: **1)** harvesting module, **2)** power management module (which contains the energy storage) and **3)** the sensor module. The detailed presentation of the hardware is out of the scope of this paper, only an overview will be presented. Details can be found in [1]. Using only solar-cell harvesting indoors is not the usual solution [11], but if the energy demand is low, it can provide sufficient energy, even at low illumination levels. Two DC-DC converters (Fig. 2.) are used in order to utilize the whole storage capacity. The storage is an electric double-layer capacitor (EDLC), which will be charged to its maximal voltage, if the circumstances are allowing it. The second DC-DC converter creates the proper voltage for the sensor unit.

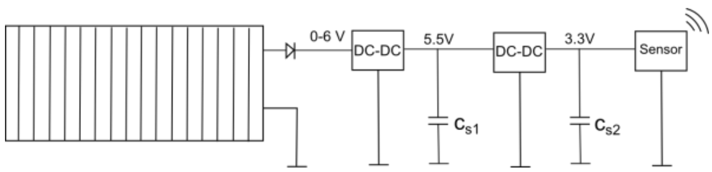

Figure 2. Block diagram of the sensor node

The sensor block (Fig. 2.) comprises of 3 parts: **1)** the sensor, which is able to measure a physical quantity, **2)** a processing unit and **3)** an RF transceiver (details in [1]). Various sensors can be used, e.g. passive infrared (PIR) sensors for motion detection, temperature and humidity and other environmental sensors. Our method is applicable to track changes in environmental quantities also, not only motion tracking which application later will be presented as a demonstration.

During the tests of the previously presented sensor 2 voltages were measured, the storage capacitor's voltage (C_{S1}) and the buffer capacitor's voltage (C_{S2}). The first test has taken place without the solar-cell, we have pre-charged the storage capacitor, and measured the discharging, with various sleep times. The voltage of the storage shows a linear decrease in time, because the constant current consumption nature of the sensor module. This linearity is advantageous, when we make an estimation of the remaining stored energy. The results of these measurements were used later when a sensor network consisting of 20 motion sensors were simulated.

III. SCHEDULING

In section II. sensors were shown with very low energy demand and with the ability to harvest the needed energy. It can operate battery-lessly if the sampling time and the harvested power allow it.

We have a weak and varying energy source (harvesting), so the lifetime of the sensor depends on how we expend the harvested energy. $E_C(t)$ depends mainly on the active time of the sensor; therefore scheduling means the control of the sleep period. If one sensor sets its own sleep period, based on the self energy storage level measurement, it is called **local scheduling policy**, and when a central coordinator sets the sleep times for all sensors based on the entire network's state, it is called **global scheduling policy**. It should be emphasized that when the central coordinator manages a global policy, it can result in different sleep times for different sensors. Mixed policies can be used as well, if in some cases the local policy can override the global directive.

A. Local policy

Let us consider a $T_S = P_L(V)$ local policy function which gives the next sleep period time from the voltage argument. $P_L(V)$ can be a continuous logistic shaped function, or a discrete look up table (LUT). A typical example of a local policy function:

$$T_S = P_L(V) = T_{\max} - \frac{(T_{\max} - T_{\min})}{1 + e^{-F\cdot(V - V_{center})}} \tag{3}$$

where V is the actual storage voltage measured, T_S is the next sleep time, $T_{\max}$ and $T_{\min}$ are the maximal and minimal allowed sleep times, F is a parameter defining the steepness of the curve, and V_{center} is where T_S equals the mean of $T_{\max}$ and $T_{\min}$. Of course the parameters of the local policy function can be different for each sensor.

B. Global policy

If our only goal is to keep alive all the sensors as long as possible, we can reach good results using only a voltage dependent local policy above mentioned. But it can deteriorate the precision of measurements reached using the WSN, if the sleep time of some sensors is too long. (In extreme situation there will be no measurement at all, it gives the best life time for a selected sensor.) On the other hand if the sleep time is short (because momentarily there is enough energy stored) the sampling frequency can be unnecessarily high.

Therefore global policy is to be used for scheduling the measurements of the sensors. This global policy even for one sensor only should be more complex than the previously shown local one. It should take into account the

- energy available (based on the storage level),
- the state of the other relevant sensors in the network,
- the possible future events to be measured,
- the possible future events that modify the available energy. (e.g. sunrise is expected, more energy will be available for harvesting).

To deal with these different aspects the modeling of the system is desired. The unknown variable (e.g. the position, movement of the person) is modeled as a Markov process. Because WSNs used in AAL applications have a very limited computational capacity, and real-time operation is required, for the sake of simplicity the basically continuous variables (spatial positions, temperature, humidity etc. and the time) are used in a quantized manner.

The following notations will be used:

- k is the (discrete) time,
- $X = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N\}$ is the set of possible states,
- $S = \{s_1, s_2, ..., s_M\}$ is the set of sensors,
- $O_i = \{o_i^1, o_i^2, ..., o_i^L\}$ is the finite set of symbols the ith sensor can provide,
- $y_i(k) \in O_i$ is the measured value of the ith sensor in time k
- $S(k) = \{s_{k1}, s_{k2}, ..., s_{kP_k}\} \subset S$ is the subset of the sensors used in time k (P_k can be different for each time step, $P_k=0$ is possible),
- $\mathbf{Y}_k = \left[y_k^1, y_k^2, ..., y_k^{P_k}\right]^T$ is the observation vector of the P_k sensors used in time k.
- $\mathbf{Y}_{1:k} = \left[\mathbf{Y}_1, \mathbf{Y}_2, ..., \mathbf{Y}_k\right]$ is the observations used from the beginning to the current time.

The model is described by the state transition probabilities $p(\mathbf{x}(k+1)|\mathbf{x}(k))$, and the measurement characteristics (depending on the topology of the sensors, and the measurement noise). The general approach known as POMDP (Partially Observable Markov Decision Process) is used for the sensor selection [9].

There are two steps:

1) The best possible estimate for the unknown variables (**X**) should be obtained, based on the previously collected information.
2) The subset of sensors to be used in the next steps should be determined, based on the information available until the current time.

The estimation of the unobservable variables can be obtained using the recursive formula:

$$p(\mathbf{x}_{k+1}|\mathbf{Y}_{1:k+1}) = \alpha \cdot p(\mathbf{Y}_{k+1}|\mathbf{x}_{k+1}) \cdot \sum_{\mathbf{x}_k} p(\mathbf{x}_{k+1}|\mathbf{x}_k) \cdot p(\mathbf{x}_k|\mathbf{Y}_{1:k}) \tag{4}$$

where α is a normalization factor.

In AAL applications both the number of sensors to be used and the number of states are in the range of 10…100 (see the demonstrative example in chapter IV.). Therefore in a typical AAL scenario the state transition matrix $p(\mathbf{x}_{k+1}|\mathbf{x}_k)$ is of tractable size (usually not more than 10000 possible state transitions are to be managed). On the other hand the matrix characterizing the measurement symbol probabilities, $p(\mathbf{Y}|\mathbf{x})$, can be unmanageable. Having only 20 binary sensors and 50 states, the number of probabilities needed is $50\cdot 2^{20}$, which is about 50 million. If we have quantized (but theoretically continuous) signals as well the situation becomes even much worse. Therefore one of the problems is how to reduce the used part of $p(\mathbf{Y}|\mathbf{x})$ such a way, which describes the system properly, but it has workable size. Fortunately the scenario is typically divided to smaller, separate parts (i.e. rooms), therefore there are close connection between some states and some sensors. E.g. if the position of the person is the unknown variable, the motion detectors of the currently used room are important; the sensors of the other rooms are not too relevant.

The sensor selection functions as follows: in each k time we can calculate a cost for each of the $\{s_1, s_2, \ldots, s_M\}$ sensors. The cost function comprises of three parts. Relevance of the sensor according to the most possible states are affected by the highest values from $p(\mathbf{x}_k|\mathbf{Y}_{1:k})$. The second term corresponds to the sensor's current stored energy level. The third **optional** term represents the result of a prediction, with this we can achieve that a sensor's sampling time will be prepared for detection of a possible future event; and can take into account the energy harvesting possibilities caused by this event. A cost function is formulated in the following form:

$$C_{i,j,k} = \frac{1}{R(i,j)} + \frac{\alpha}{P_0 + P_S(i,k)} + \beta \cdot F(i,k) \tag{5}$$

where $i \in \{1, 2, \ldots, M\}$ (sensor index), $j \in \{1, 2, \ldots, N\}$ (index of the most possible state), R(i,j) is a relevance function, this depends on the actual application of this method, detailed in chapter IV. The reader should note that R(i,j) is independent of the k time. $P_S(i,k)$ is the actual power stored in the ith sensor node at time k. F(i,k) is an **optional** term which represents the result of a prediction, with this we can achieve that a sensor's sampling time will be prepared for detection of a possible future event. α and β are parameters of the cost function, that determines the proportions of the different terms. Determination of the parameters depends on the actual application or the actual operation mode e.g. precision or energy sensitive operation. The sensors will be selected are the ones with minimal cost. (P_0 is used to avoid the possible zero value of the denominator.)

IV. Demonstrative Example

The ideas shown in previous sections could be demonstrated with our test example, which is a simulation of a home health monitoring system. It is used to infer the activities of daily living, and for that reason the motion (so the position) of the patient is to be detected at home. The WSN of our test case consists of motion sensors. We used real life measurements to provide proper consumption values for the simulation, these values are the following (measured in the sensor proposed in section II): the length of a measurement followed by data transmission is 1 second; the currents are 16 mA in transmission mode, 200 µA in measurement mode and 7 µA in sleep mode. It should be recognized that transmission is one of the most important factors affecting the energy consumption.

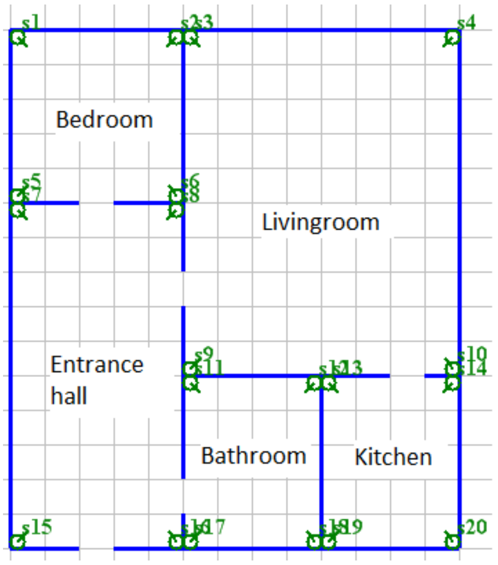

Figure 3. The arrangement of the simulated environment, and the motion sensors (s1…s20).

The test home used is shown in Fig 3. Activities of the person were simulated for a 10 days long period. We collected the positions of the person, and the signals of the motion sensors. The possible activities of the person were:

- Dining: breakfast, lunch, dinner
- Toilet and bathroom usage
- Going away from home
- Reading, resting in chair
- Sleeping at night

The sequence and the length of the activities were controlled in the simulator by simulated physiological needs (tiredness, thirst, hunger etc.). E.g. if the hunger (increased by the time and the physical work done) is high enough: the breakfast, the lunch or dinner will be simulated depending on the time. These eating will decrease the hunger; therefore the priority of eating drops and a different activity could start. There are random events and circumstances, the resulting sequence will not be the same in each day. (There will be breakfast, lunch and dinner, but the timing and length of them, the resting, bathroom usage etc. could be different from day to day.) These activities produced a motion sequence (e.g. moving from the living room to the kitchen etc.), which was stored and used by the simulation of the sensor network.

A. Building the model

By using the POMDP methodology presented in the previous chapter, we will solve a target position tracking problem, where the scheduling of the motion sensor data transmissions are optimized the energy consumption and the achieved precision in the position measurement. In Fig. 3. the test apartment is shown, it has 5 rooms, and has 4 motion sensors in each room. For the simulation we subdivided the rooms to 9 subsections (Fig.4.) We can define the states of the Markov process in 3 ways:

- Using individual processes with 9 states for each room, and in each step using the only one in the active room. (The active room is where the last movement happened.)
- Using connected processes for the rooms, which have additional states to describe that the target is not in the room.
- Using one global process with 5·9=45 states (room number times the number of sub states), to describe the whole area.

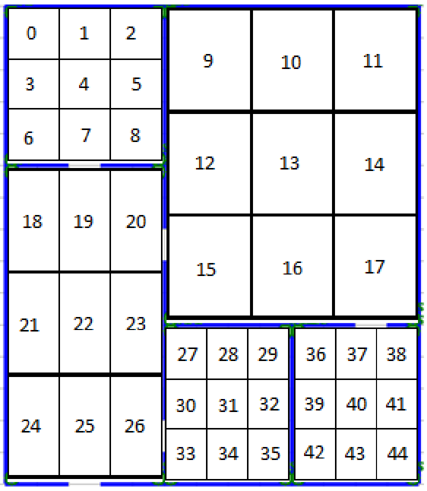

Figure 4. The subsections of the rooms, as the possible states of the model.

In our simulation we used the third option, because the state space is still the size we can handle. To model the state when the person is not in the apartment, an additional 46th state is added.

The notations presented in chapter III. will be the following for this actual example:

- k is the (discrete) time,
- $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_{46}\}$ is the set of possible states,
- $S = \{s_1, s_2, \ldots, s_{20}\}$ is the set of sensors used,
- $O_i = \{0,1\}$ is the finite set of symbols the ith sensor can provide

We have to define the state transition matrix (A):

$$\mathbf{A} = \begin{bmatrix} P(s_k^1|s_{k-1}^1) & P(s_k^2|s_{k-1}^1) & \ldots & P(s_k^{46}|s_{k-1}^1) \\ P(s_k^1|s_{k-1}^2) & P(s_k^2|s_{k-1}^2) & \ldots & P(s_k^{46}|s_{k-1}^2) \\ \vdots & \cdots & \ddots & \vdots \\ P(s_k^1|s_{k-1}^{46}) & P(s_k^2|s_{k-1}^{46}) & \ldots & P(s_k^{46}|s_{k-1}^{46}) \end{bmatrix}$$

We used a 10-day simulation and from first 5 day we accumulated the state transitions, so the A matrix contains the most possible routes for the target. The state vector (**X**) is the following:

$$\mathbf{X}_k = \begin{bmatrix} x_k^1 = P(pos = 0|y_{1:k}) \\ x_k^2 = P(pos = 1|y_{1:k}) \\ x_k^3 = P(pos = 2|y_{1:k}) \\ \vdots \\ x_k^{46} = P(pos = 45|y_{1:k}) \end{bmatrix}$$

$$|\mathbf{X}_k| = 1$$

where k is the time index, $P(pos = i|y_{1:k})$ means the probability of the target is in "i" coded position (see Fig. 4.) if the measurements were $y_{1:k}$. We have to calculate the probability of the next state in two cases. If there are new measurements:

$$\mathbf{X}_{k+1} = \alpha \cdot diag(\mathbf{E}_k)\mathbf{A}^T \boldsymbol{X}_k \tag{6}$$

where the probability of the new measured in information represented by $\mathbf{E}_k$, this is calculated from $\mathbf{Y}_k$ and the sensor model. If there are no new measurements, we can predict one step according to the state transition matrix:

$$\mathbf{X}_{k+1} = \alpha \cdot \mathbf{A}^{\mathbf{T}} \mathbf{X}_k \tag{7}$$

B. Sensor scheduling and selection

The sensor scheduling is based on the output of the model (the most possible position) and on the actual energy state of the particular sensor. In this problem the sensor scheduling means the control of each sensor's sampling time. The sensors can operate in 3 different modes: **1)** sleep, **2)** measure and **3)** transmit. In measure mode, the sensor performs a 1 second long measurement with the given measurement sampling rate, and if the result is positive (motion) it performs a transmission to the coordinator. The coordinator has to reply with an acknowledgement and gives the new value of the measurement rate for the future. For the sake of simplicity during the simulation only two values: short interval and long interval were used. In different simulations the short interval was one of the following values: 1, 5, 10, 20, 40 seconds, the long interval was always 60 seconds. So before a transmission arrives from a sensor, we have to decide how to set the sensor's next interval. We maintained a list of the so called active sensors (the one's with short interval). The list is based on the cost function:

$$C(i, j, k) = \mathrm{dist}(i, j) + \frac{\alpha}{\mathrm{voltage}(i, k)} \tag{8}$$

where i is the sensor index, j is the index of the most possible state, α is a tuning parameter. The distance function defines the relevance of the sensor according to the most possible actual position of the target. The distance is calculated using the state transition matrix (**A**): the shortest possible path from the actual most possible state (position) to the state closest to the sensor is searched for. The distance function results in a value inversely proportional to the relevance of the sensor to the estimated state, see (5). We can calculate that how many state transitions are needed from the actual most possible state to get in a state closest to the sensor. Optionally we can weight this number with the probabilities of these state transitions. We can substitute this calculation with a look-up-table, because it is independent from the actual time k. The sensor's energy level is represented by the voltage of its storage capacitor. It is a good estimate, due to the linear voltage curve of a capacitor when continuous current is drawn from it (proven by measurements in [1]). We will put on the active sensor list the first L sensors with the lowest cost. L is a parameter of the model. Optionally L can be substituted with a cost limit parameter. We calculate the costs to create an active sensor list in every k moment, but the particular sensors will be reconfigured only when a transmission exchange is performed with the coordinator.

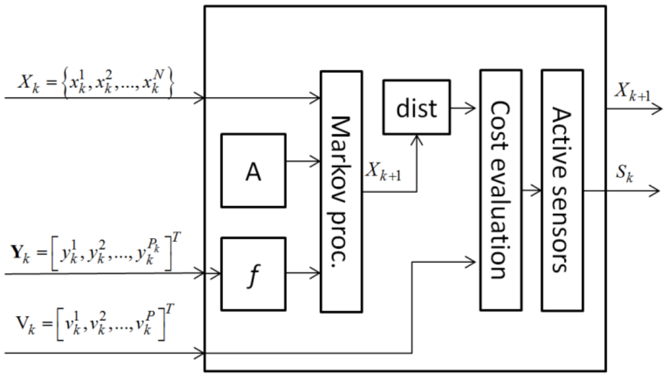

Figure 5. The block diagram of the system proposed for the actual application (V_k is the storage voltages of the sensors operated at k, S_k is the vector of the sensors reconfigured in the time k).

C. Simulation

With the simulation we would like to measure the sensor network's performance in measurement precision and energy consumption, which are inversely proportional to each other. The precision is calculated from the distance between the estimated position and the simulated position. If we use all the sensors set to continuous measurement, we will get the most accurate estimation, so we will compare the other results to this.

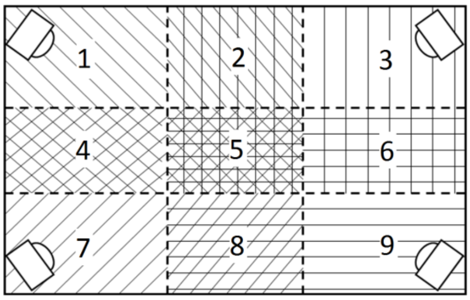

Figure 6. The layout of the sensors in a room, the simplified area of detection for each sensor is shown using different stripping.

As mentioned before each room has 4 motion sensors, so we can localize the motion within a room in 9 subsections (Fig. 6.). If all the sensors detect motion, the target is in the central area 5. If two of them detect the person then it is either in area 2 or 4 or 6 or 8. If only one sensor detects the motion then one of the areas 1 or 3 or 7 or 9 is the section of interest. In this simulation it is assumed that the sensors measuring distance is calibrated to the center of the room, so when all the sensors in a room are sensing motion, the person is in the center section of the room. The energy consumption for a sensor is calculated from the time spent in sleep mode, the number of measurements and transmissions performed during the simulation. We also simulated the harvested energy amount for each sensor, this depends on the time of the day, and whether the target is in the room or not.

To evaluate the results of the proposed method we defined some basic scheduling policies, these are the following:

- Fixed: Using only the short interval for all sensors.
- Simple: Maintains active rooms (where the last measured motion happened) and passive rooms. The sensors in the active room are set to short interval, others are set to long interval.
- K-nearest neighbor: If a sensor detects motion, the K nearest sensor are set to short interval, the further ones are set to long interval.
- Time of day (predictive): In maintains a rough statistic about the daily pattern of the motions in the apartment, e.g. the night time when there is fewer motion events, in these periods all the sensors are set to long interval.
- Hybrid: Combines the K-nearest neighbor with the time of day scheduling.

We simulated all these methods with 1, 5, 10, 20, 40 second short intervals, and a fixed 60 second long interval.

D. Results

The results of a 10 day simulation are presented in Fig. 7. and Fig. 8. In the first 5 days only the **A** transition matrix was learned. The error is calculated from the distance of the center points of different subsections and it is averaged over the time. As expected the fixed measurement interval method produced the most accurate estimation in position, but it also has the highest energy demand. The time-of-day method is worth mentioning from the basic methods. It produced remarkable better results than the other basic methods, but it is due to the used a priori information (night time and day time). The HMM method produced even better results (especially in consumption), and it did not utilized a priori information, the state transition matrix generated on-line.

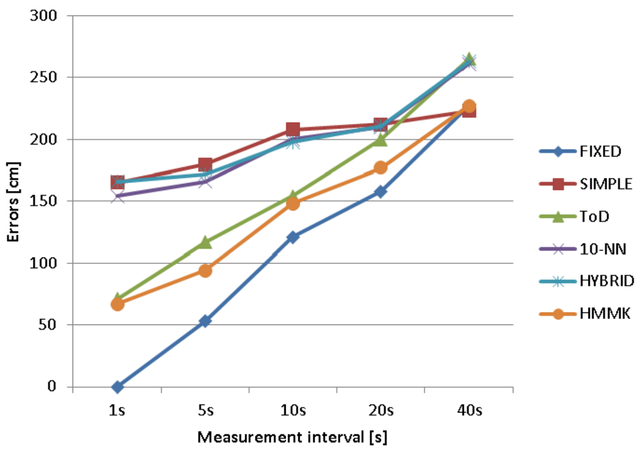

Figure 7. The resulted errors of the simulations, scheduling methods with different measurement intervals.

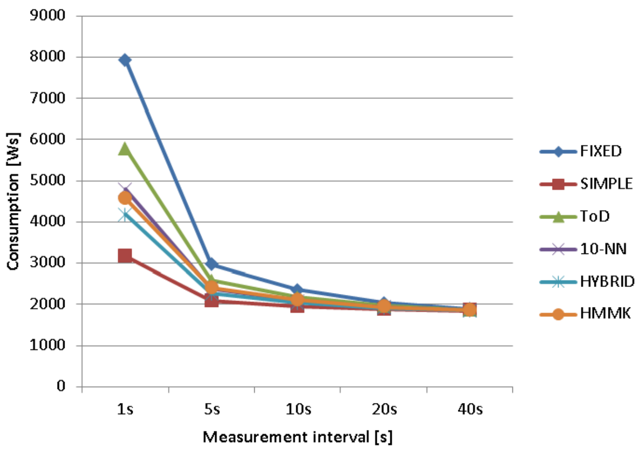

Figure 8. The consumption results of the simulations, scheduling methods with different measurement intervals.

V. Conclusion

A method for measurement scheduling in WSNs used in AAL applications is proposed. The method is based on a Hidden Markov Model of the unknown variables to be measured, and tries to optimize together the energy consumption of the WSN and precision of the measurement using a complex cost function. The most important suggestions are the following:

- The active reception mode of the sensors is as costly as data transmission, which is responsible for the major part of the energy consumption. Therefore a sensor is configured only in the acknowledgement message after its measurement message arrived, in other time intervals it is in sleep mode.
- The actual and predicted future states of the observed system variables and the environment are estimated as well. The state of the system is important because the relevance of a sensor varies in different states. The state of the environment is important because sustainable operation is the goal, and the state of the environment affects the harvestable energy
- Taking into account that sometimes the selection of the relevant sensors is delayed, the system should prepare itself for different possible states, using a wider set of sensors for maintaining the precision.

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