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Wireless Sensor Networks Framework for Indoor Temperature Regulation

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Abstract. Wireless Sensor Networks take a major part in our everyday lives by enhancing systems for home automation, health-care, temperature control, energy consumption monitoring etc. In this paper we focus on a system used for temperature regulation for homes, educational, industrial, commercial premises etc. We propose a framework for indoor regulation and optimization of temperature using wireless sensor networks based on ZigBee. Methods for optimal temperature regulation are suggested and discussed. The framework is based on methods that provide energy savings by reducing the amount of data transmissions through prediction methods. Additionally the framework explores techniques for localization, such that the location of the nodes is used for optimization of the temperature settings. Information on node location is used to provide the most optimal tradeoff between the time it takes to reach the desired temperature at a specific part of the room and energy consumption.

Keywords: temperature optimization, wireless sensor networks, ZigBee

1 Introduction

Wireless sensor networks (WSN) are able to efficiently sense various information with high accuracy and low power consumption. The development of sensors and networks based on sensors has impacted and changed everyday life and work. Engaging WSN in home and industrial monitoring systems, medicine and health-care systems, entertainment, education etc. has enlighten and improved processes in overall. A wireless sensors consist of three major elements [1]: sensor unit (used to measure the parameter), computing unit (used to process data) and communication unit (based on radio communication). Different radio technologies can be used such as: ZigBee, Wi-Fi, Bluetooth, GSM etc. ZigBee as an emerging technology has been proven to make WSN self-configurable and self-healing while operating at low power consumption [2].

Intelligent smart home frameworks have been proposed recently by the research community in [3] and [4]. The proposed systems are used to monitor and report different home parameters such as: temperature, humidity, light and in order to control different electrical devices: lightning, aircondition, heaters. In [4] energy optimization is based on a dynamic programming algorithm that will control the usage of energy and sell it back to the smart grid.

This paper proposes a Wireless Sensor Network Framework for Indoor Temperature Regulation (WSN-FITR). Homes, classrooms and halls are often heated up by a number of temperature controlled heaters. Users are usually not interested in controlling the temperature at each separate heater. The radiators for examples are normally located just above the floor/below windows and at the room's walls and furthermore the measurements don't show the real room temperature as the temperature sensors are located just next to the heater. Neighbouring rooms with own heating elements also influence the temperature in the controlled room. This paper shows how the node localization methods can be used for room temperature optimization in order to provide the most optimal tradeoff between the time it takes to reach the wanted temperature at a specific part of the room and energy consumption. The distance from the heaters to other networks and their temperature influence is important for saving the overall energy consumption. Even more, reduction of the required data transmission through prediction methods is considered. This is important in order to increase the battery life of the nodes and to extend the network lifetime.

The rest of this paper is organized as follows. In the second section, the framework architecture od WSN-FITR is presented. Section 3 gives a detailed explanation of techniques for indoor localization and clustering with respect to characteristics of the environment where WSN is deployed. Section 4 compares techniques for data reduction in WSN. Finally, we conclude this paper in the last section.

2 System Architecture

The proposed WSN-FITR system for indoor temperature regulation is consisted of two basic elements: sensor-regulators and temperature controllers which are inter-connected in a ZigBee network. In wireless sensor network the sensors-regulators are known as nodes and the controller is referred to as sink nodes. Deployment diagram of the framework is given on Fig. 1.

Sensor-regulators perform measurement and reporting local temperature readings to the controller. They are attached to a device and regulate its action (for example increase/decrease heating) in order to reach a certain temperature. Typical devices and their corresponding actions are:

- **Heating bodies** such as central heating radiators, electric radiators or fans. The regulator can increase/decrease the heating by using the valve controller.
- **Air conditioners** which can be based on a fan. The regulator can increase/decreasing the cooling volume in order to reach a certain temperature.
- **Air flow** such as central air flow ventilation. These devices can regulate the degree of air circulation.

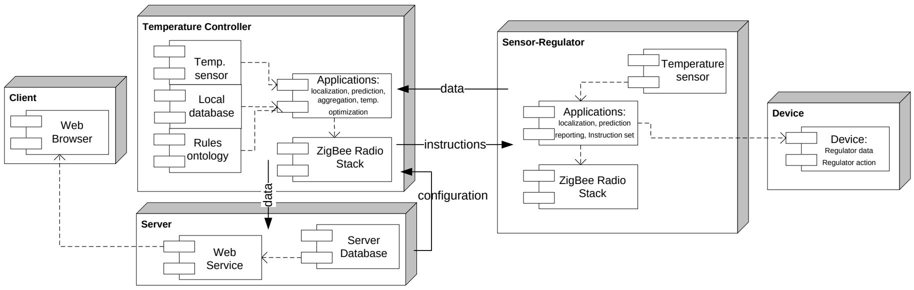

Fig. 1. Deployment diagram of the system.

- **Window shutters** such as outside curtains. By rising/lowering the curtains the influence of the sun energy can be regulated.

The temperature controller nodes are considered more powerful than the sensor-regulators. They are expected to have more advanced capabilities: memory, processing unit and steady energy supply. They should be located higher up in the room and away from all the heaters and windows in a location that better represents the room's temperature in order to measure the most relevant temperature. Additionally they are used to control the temperature at the premises where the device is placed by generating instructions for regulation. Temperature controllers represent the sink element where the information is gathered and locally analysed. Two different types of information are considered static and dynamic. Static data is related to one-time information such as location (in 3D) and type of nodes. Dynamic data is related to time variable parameters such as temperature, energy cost etc.

As illustrated on Fig. 1, the temperature controller consists of the following elements: local database, rules (which can be based on ontologies [5]). Client should be able to remotely configure the rules so the controller can meet the temperature goals. The rules can include for example temperature levels for several time intervals during different days. The local database at the controller can be used in order to store information regarding the temperature readings, as well as the static information such as node type and locations. The database can further contain information on the size of the room being monitored, the number of expected visitors and other factors that can influence the temperature changes. All information that can not be obtained from the nodes, such as electricity cost, can be obtained from the server. Additionally the server contains database that can be used by the controller to store historical data.

2.1 Temperature Optimization Framework

Finally a temperature controller needs to make decisions by generating a set of instructions for the different nodes by running a regulation method. This method is required by the controllers in order to achieve distributed decision regarding the temperature difference that need to be achieved in a certain point in order to satisfy the required overall temperature.

In order to provide a self-organized and cost-effective solution, the WSN must provide the following functionalities: self-localization, nodes clustering, data prediction, distributed decision making etc. Sensor readings are useless if the location where they are measured is not known. Thus, a suitable localization algorithm should be implemented in order to discover the location of the nodes.This is important because manual recording of the nodes positions is very time consuming solution and prone to errors. The location information will be used by the controller device to deduct the temperature set-point that each of the heater shall be commanded to, so that the temperature dissipation from all heater gives the wanted temperature at the controller's location and the controlled premises in overall (elaborated in section 3). After nodes discovering phase, nodes can be divided into clusters. There are many algorithms purposed in the literature for optimal nodes clustering. For now we assume that nodes deployed in close proximity to each other belong to the same cluster.

After these two phases (discovering and forming the clusters), we consider that WSN is established. Nodes can start measuring the temperature and forwarding the measured readings to the final destination (sink node). In order to save energy, algorithms for data prediction should be implemented on both sides: node and sink (elaborated in section 4).

The temperature measurements are analysed by generation of temperature gradients. The temperature gradient indicates the direction and the rate at which the temperature changes within a particular location. The dynamic information such as temperature gradients, time of the day, expected visitors, electricity cost and the static information such as node type represent input to the temperature optimization method.

The location and temperature prediction methods allow the calculation of the temperature gradient. Several methods can be used in order to rank or assign weights to the different types of input such as Multiple Attribute Decision Making algorithm, Genetic Algorithms, Analytic Hierarchy Process, Fuzzy logic. Fuzzy logic is suitable as fuzzy judgement matrices used for the comparative analysis are close to the way the humans reflect and are very easy to implement. The Fuzzy Inference System can be based on the standard Mamdani or Sugeno. For each parameter that needs to be taken into consideration membership function needs to be defined. Additionally the rules that need to be applied need to be carefully chosen. The actual definition of the membership functions and the rules will be considered in our future work.

After the collected data is analysed, the controller sends instructions to the nodes (regulators). The instructions are represented by the temperature difference that the node should achieve. If the temperature needs to be increased, the nodes perform an action such as increasing the heating energy.

2.2 WSN-FIRT network topology

ZigBee is a low-cost, low-power, wireless mesh network standard. The low cost allows the technology to be widely deployed in wireless control and monitoring applications (in fields such as home automation, health-care, temperature control etc.). Low power-usage allows longer life with smaller batteries. Mesh networking provides high reliability and more extensive range. ZigBee operates in the industrial, scientific and medical (ISM) radio bands; 868 MHz in Europe, 915 MHz in the USA and Australia and 2.4 GHz in most jurisdictions worldwide. Data transmission rates vary from $20kbps$ in the 868 MHz frequency band to $250kbps$ in the 2.4 GHz frequency band.

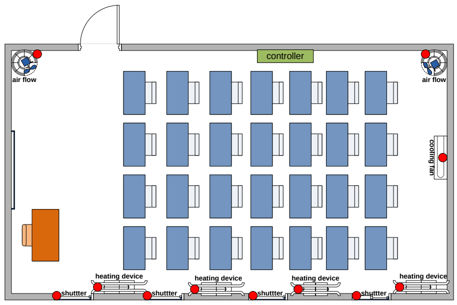

Fig. 2. Star architecture for a typical classroom.

The ZigBee network layer natively supports both star and tree network topologies, and generic mesh networks. Every network must have one coordinator device, tasked with its creation, the control of its parameters and basic maintenance. Within star networks, the coordinator must be the central node. Both trees and meshes allows the use of ZigBee routers to extend communication at the network level. Since the routers need to be constantly on listening for network traffic, it is normally assumed that the routers are mains powered sensors/devices and the battery devices are assumed to be sleeping and only waking up and polling for data periodically or on demand (upon user interaction).

The network topology should adapt to the characteristics of the controlled premiss. For the proposed WSN-FITR we consider two different topologies: star and cluster-based. An example of a star topology is illustrated in Fig. 2 where one classroom is illustrated. In this case there is a single temperature controller that is responsible for controlling the temperature at the different nodes. The star topology is most appropriate for small areas where there are no major obstacles so that the signal from the nodes does not fade in high extend. For large premisses, cluster based topology is preferred over mesh as in the latter higher energy is required at the nodes due to the fact that each node transmits its own readings and the readings of other nodes. Fig. 3 illustrates the proposed WSN-FITR for one floor in a commercial center. In this case there are several temperature clusters that are controlling a set of nodes. The decision regarding

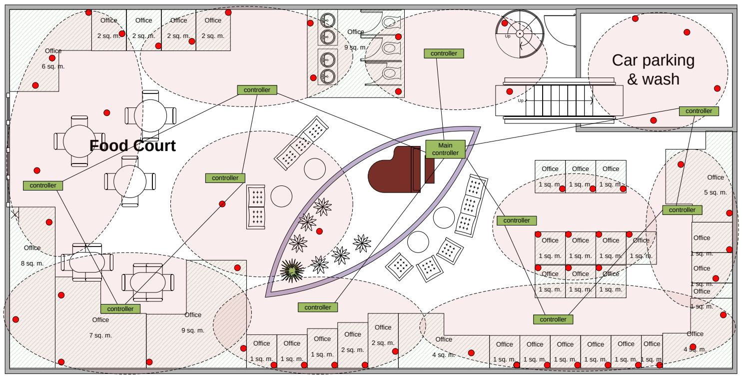

Fig. 3. Clustered architecture for one floor in a shopping center.

the temperature regulation is distributed among all controllers. There is one main controller that has wired connection to the server in order to retrieve/store information towards the database at the server.

3 Localization and Clustering in Indoor WSN

Many algorithms have been proposed for ZigBee based WSN localization. Most of them consider a WSN deployed in outdoor environment where GPS signals are available and a global map of the network can be easily achieved using well known techniques for localization. On the other side, indoor localization methods should consider different characteristics of the indoor surroundings where WSN is installed. Finding position of indoor WSN is more challenging since GPS signal is heavily attenuated by building structures such as walls and roofs and there is absence of line of sight to some satellites [6]. With only few exceptions, the distances between the nodes of the network are necessary to be known for accurate location prediction. Different techniques are used to obtain the distances:

- RSSI (Receive Signal Strength Indicator)
- ToA (Time of Arrival)
- AoA (Angle of Arrival)
- TDoA (Time Difference of Arrival)

The techniques based on RSSI are easier to implement and don't require additional hardware, as all standard wireless devices possess features for measuring this value. But finding the relationship between the signal strength attenuation and the transmission distance in indoor environments is not a trivial task [7] [8]. Additionally, many other characteristics of indoor environments have to be considered, like temperature and humidity variations, furniture rearrangements, presence of human beings, etc.

Indoor localization methods can be divided into two main categories [9]:

- deductive methods. They take into account only the physical properties of signal propagation. They require the positions of the access points, radio propagation model and map of the environment.
- inductive (fingerprinting) method. They require a previous training phase where the system learns the RSS in each location. This phase can be very time consuming. In the next (positioning) phase, different matching algorithm can be used in order to find the unknown location.

In [9] the authors present an algorithm that combines the advantages of both deductive and inductive methods. This hybrid method reduces the training phase without a loss of precision. In [10] several matching fingerprinting algorithms are investigated: the nearest neighbor (NN) algorithm, the K-weighted neatest neighbor (KWNN) algorithm and the probabilistic approach based on the kernel method. Through simulations it has been shown that KWNN algorithm has the best indoor positioning result.

Since localization is very crucial in our WSN-FITR, the algorithm should be selected very carefully in accordance with the characteristic of the environment where the network should be deployed. If there are many walls and obstacles in the environment, the deductive methods should be avoided because they estimate the position mathematically. When there are multiple access points and few walls in the environment, inductive methods are not necessary as the training phase can be very expensive.

After determining the location, sensor nodes in WSN can be geographically grouped into clusters. In each cluster one representative node (cluster-head) is chosen to coordinate member nodes. The main advantages of WSN clustering is not only to prolong the WSN lifetime, but also to establish collaboration between cluster members in order to provide data aggregation and more accurate reports about the region they sense. Many algorithms have been proposed in the literature for WSN clustering [11] [12].

4 Reductions of Data Transmissions

By reporting data measurement at each interval, WSN nodes consume a great deal of energy, which reduces its lifetime and creates sufficient communication overhead. Several techniques have been developed to overcome these problems i.e., to lower the communication overhead and to increase energy saving. Most of them consider reducing the number of radio transmissions.

Three main paradigms can achieve reduction of radio transmissions:

- *data compression;* where well known compression techniques are used to compress consecutive measurements. This approach is useful only if the WSN application doesnt require the data in real-time.
- *in-network processing;* when data are processed on their way to the sink. This method is usually performed when summarization functions or other queries are needed. It is appropriate only for mesh-based, cluster-based or hybrid-based network topologies.

- *data prediction;* when different prediction methods are used for predicting next sensor readings. Here, each node runs a filter (or a model) that estimates next sensor reading. The sink runs exactly the same models for each sensor in the network and makes the same predictions. This approach is known as Dual Prediction Scheme (DPS).

For the WSN-FITR system we want sensor measurements up-to-date, hence data compression is not an appropriate solution. Regarding network topology, we can choose among data prediction and in-network processing. If the network topology of WSN-FITR is star-based, we should apply data prediction methods. For different topologies we should consider in-network processing or combination of both.

In order to compare these techniques for data reduction, different algorithms were implemented in MatLab. For the evaluation, a set of experimental data from Intel Lab [17] was used. The 54 Mica2Dot sensors deployed in the laboratory were equipped with weather boards and measured temperature once every 31 seconds. The measurements were collected between February 28th and April 5th, 2004. We run the simulations for 50 different error margins eMax (ranging from 0.1°C to 5°C).

4.1 Data prediction using LMS-VSS

The most appropriate models (filters) for DPS are based on time-series forecasting: Moving Average (MA), Autoregressive (AR) [13], Autoregressive Moving Average (ARMA) [14], Least Mean Square (LMS) [15] and LMS with Variable Step Size (VSS-LMS) [16]. We implemented and evaluated LMS, LMS-VSS, second-order MA and ARMA. Fig. 4 shows the reduction gain for each of these algorithms simulated on two nodes form the Intel Berkeley Research Lab network [17]. The metric is the reduction of transmissions in percentage (Fig. 4, upper) and the difference between the predicted and the true value (Fig. 4, lower), i.e. mean square error (MSE).

4.2 In-network processing in WSN-FITR

For cluster, mesh and hybrid-based network topologies, each sensor readings should be retransmitted at least twice, so data reduction is expected to be smaller compared with star-based topology. But if WSN in deployed on vast region, the network can not be organized as star-based since radio signals are far from the sink and multi-hop routing is the only way for data to reach its destination.

In order to calculate the reduction in this case, we divided Intel network [17] into clusters (Fig. 5). Two algorithms were used for evaluation, LMS [15] and LMS-VSS [16]. The clustering parameter was geographic position, i.e., Euclidian distance. We assume that each sensor sends its reading to the cluster head, responsible for resending the reading to the sink. As a result, each reading is sent twice, except the readings taken at the cluster head. Additional reduction can be

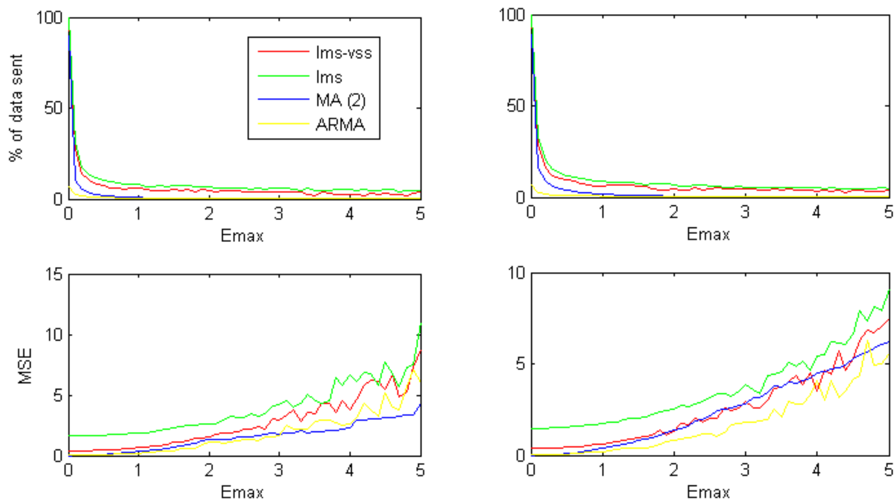

Fig. 4. Data reduction for different algorithms for Node 13 (left) and Node 49 (right).

achieved if cluster head performs summarization function (Average, Minimum, Maximum, etc.) and forwards only the calculate aggregate to the sink.

Fig. 6 shows the reduction for cluster containing nodes: 7, 8, 9, 10, 11, 53 and 54. LMS-VSS shows an average gain of 5% compared to LMS algorithm. When cluster head performs data aggregation, the data reduction is far greater (97% reduction of the total messages sent for the given error margin of 0.5°C).

5 Conclusion

In this paper we propose WSN framework for indoor temperature regulation. We give an overview of the methods that can be used for nodes localization and clustering in ZigBee-based network. In order to reduce the energy consumption, we propose data reduction strategy based on dual prediction scheme that uses Least Mean Square filter as a prediction method. Through simulations on real world dataset we show that this filter is good predictor for temperature readings.

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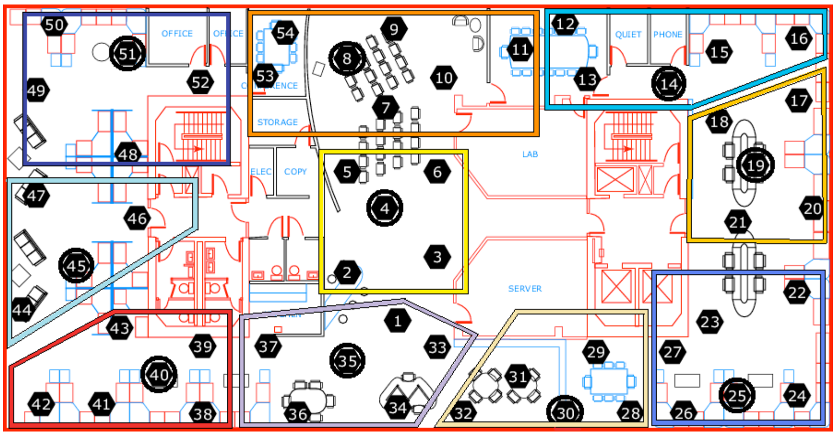

Fig. 5. A clustered view of the Intel Lab [17].

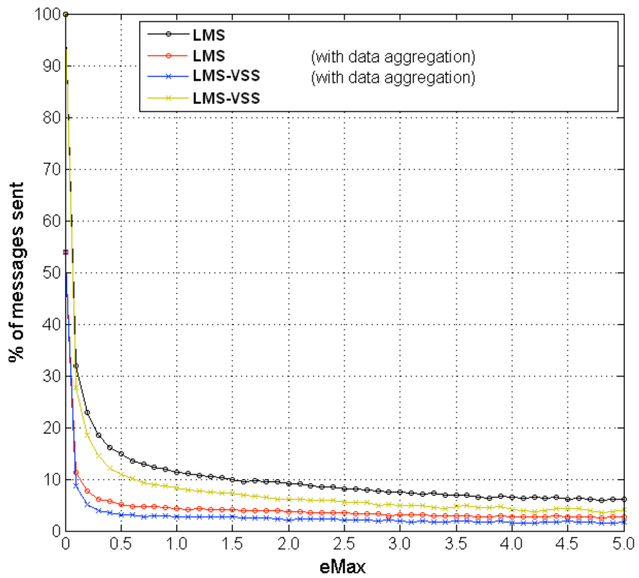

Fig. 6. Data reduction in the cluster containing the nodes: 7, 8, 9, 10, 11, 53 and 54.

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