Doctoral dissertation title:

Learning based Adaptive Sensor Selection Framework for Multi-Sensing WSN

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Abstract:

Wireless sensor networks are gaining enormous attention for monitoring physical conditions in various applications. The network consists of many densely/sparsely deployed wireless sensor nodes. The field-deployed battery-powered sensor nodes equipped with power-hungry sensors often suffer from limited energy availability due to the limited battery capacity. The energy consumption is higher for the sensor hubs equipped with multiple sensors monitoring multiple parameters in the environment. To this end, this dissertation aims at developing efficient smart sensing approaches to enhance the energy sustainability of such WSNs. A sensor node equipped with a sensor monitoring the variation of a particular parameter in time often exhibits a high temporal correlation that has been exploited in this study to smartly sense the parameter. In the case of a multisensing node, the signal variation of multiple parameters sensed in the same environment possesses a good cross-correlation among them, which has been exploited to optimize energy consumption in a multi-sensing node.

As a first step, a learning-based optimization strategy is developed for a multi-sensing node using Upper Confidence Bound algorithm to select an optimum active sensor set in a measurement cycle based on the cross-correlations among the parameters, energy consumed by the sensors, and the energy available at the node. Further, a Gaussian process regressor-based prediction model is used to predict the parameter values of inactive sensors from the cross-correlated parameters of active sensors. To evaluate the performance of the proposed framework in real-life applications, the algorithm has been implemented in an air pollution monitoring sensor node consisting of seven sensors. The node has been deployed on the campus of IIT Delhi. It has been observed that the proposed algorithm significantly reduces the energy consumption of the node.

Further, to optimize the sensing energy consumption of each sensor in the node, a learning-based adaptive sampling framework is developed that explores the sparsity in the time series data and finds optimal sampling instants for the next measurement cycle. The principal component analysis is used to sparsify the time domain signal and the sparse signal is reconstructed from its low-dimensional signal using the sparse Bayesian learning method. An optimization function is formed that solves the trade-off between accuracy and energy consumption and finds the optimal sampling instants for the next measurement

cycle. The simulation results validate that the proposed smart sensing method significantly reduces the sensing energy consumption of the individual sensors in the node.

In the next study, a novel edge intelligence-based data-driven dynamic priority sensing and transmission framework is developed to optimize energy efficiency as well as sensing accuracy. The proposed framework jointly exploits the cross-correlation among the sensing parameters and temporal correlation of the individual sensing signals to find an optimal active sensor set and optimal sampling instants of the sensors in the next measurement cycle. The length of measurement cycle is dynamically decided based on the change in cross-correlation among the parameters and the system state. A discounted upper confidence bound algorithm-based optimization function is formulated to find the optimal active sensor set by solving the trade-off among cross-correlation, energy consumption, and length of measurement cycle. The proposed framework uses Gaussian process regressor-based prediction models to estimate the temporal and cross-correlated parameters of the active and inactive sensor set, respectively. The sampling interval of each active sensor is dynamically adapted based on the temporal prediction error. Extensive simulations are performed on air pollution monitoring dataset to validate the efficacy of the proposed framework in both real-time and non-real-time applications.

The real-life deployments of air pollution monitoring systems are sparse, due to large size, high cost, and high-power consumption. Such sparsely deployed sensing stations are unable to provide a fine granular pollution mapping of a given geographical area. By deploying low cost, low power, miniature air pollution monitoring sensor nodes, the air pollution of the whole area can be accurately measured. However, accuracy of the sensed data of the low-cost miniature sensing nodes needs to be addressed. Thus, an autocalibration method of low-cost MSNs, with the help of sparsely deployed high-cost sensing stations is proposed. The datasets from the HCSSs are collected and used to calibrate the MSN using a suitable learning-based regressor model at the nearby edge node. Further, a cross-correlation based method of determining the optimum time to recalibrate the low-cost sensors in a multi-sensing node is also proposed. This method eliminates the requirement of taking the MSNs offline to calibrate/re-calibrate them. To apply the proposed autocalibration method, this paper additionally presents the design of a low cost, low power particulate matter sensor. To validate the performance of the low-cost PM sensor, the calibrated PM data are compared with the data collected from a collocated commercially available PM sensor, which is considered as a reference. The low-cost PM sensor is 91% more cost efficient and 57% more energy efficient compared to the commercial high-cost PM sensor, while maintaining the sensing error within a given threshold.