single framework. We were able to report savings of 87% in reads and transmissions, which we further increase through ARTC.

Adaptive sampling tailors the sampling frequency to the distribution of the data [8]. Padhy et al. propose a confidence-based adaptive sampling method called Utility-based Sensing and Communication (USAC) [15]. They apply linear regression to predict the next sensor value with a bounded error-range, the so-called confidence interval (CI). If a value is outside the CI, the sensor starts sampling at maximal frequency. Otherwise, the frequency decreases exponentially by a factor $\alpha \in [0,1]$ until it reaches the minimum sampling frequency.

Aiming to provide an energy-efficient solution in the realm of Big Data and IoT, Trihinas et al. propose the Adaptive Monitoring Framework (AdaM) [23]. They use an ad-hoc forecasting method called PEWMA to produce one-step forecasts, which they then use to compute the metric stream's variability.

Fan et al. propose Filtering and Adaptive sampling for Differentially Private Time Series Monitoring (FAST) [6]. They define a so-called privacy budget to add Laplace noise to the original observations to achieve differential privacy. Then they generate estimates, the quality of which is then used by the sampling component to adjust the sampling rate using a PID controller. Compared to AdaM and USAC, FAST is slower to adapt to changes in the distribution of the data but achieves comparable results.

We design our adaptive read-time tolerance controller ARTC using ideas from all three of the aforementioned adaptive sampling algorithms. We use a PID controller [3] in order to assess whether the read-time suggestion algorithm achieves the data-quality ARTC targets. Similar to AdaM, we use PEWMA [5] in order to monitor the distribution of samples. We use the idea presented by Padhy et al. of decreasing tolerances rapidly if the desired data accuracy is missed, which enables us to adapt to changes in the distribution quickly.

5 CONCLUSION

We previously developed a multi-query read scheduling algorithm that enables adaptive sampling in a sensor network [20]. In this paper, we now extend our work by proposing the easy to configure adaptive read-time tolerance controller ARTC. Our experimental evaluation shows that ARTC tailors the extent of read-sharing to the data-accuracy demands of end-applications. ARTC is generally-applicable for defining read-time tolerances when scheduling sensor read-times. Thus, it enables multi-query optimization through sharing sensor readings for arbitrary adaptive sampling techniques. We evaluate ARTC on three real-world IoT datasets with different data characteristics and shifts in the data distribution. Our solution reduces the error in the representation by up to 60% compared to fixed read-time tolerance algorithms by adapting to the sensed data's variability. ARTC not only reduces the number of reads and transmissions while achieving the same sensing error as existing techniques, but also enables multi-query read-sharing for queries issued by users without domain-knowledge. We make our code and evaluation available open-source. We also provide detailed instructions on how to execute custom experiments. In our previous work, we allow the user to define a so-called penalty-function [20] to further increase the read-sharing potential under specific circumstances. We plan to extend our solution to adaptively tune such penalty-functions based on the data's variability as well.

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