# Survey present and future visions of Internet of Things (IoT)

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**Abstract:** The main purpose of this study is a survey of present and future visions of Internet of Things (IoT). The internet of things (IoT) is the network of physical devices, vehicles, buildings and other items—embedded with electronics, software, sensors, actuators, and network connectivity that enable these objects to collect and exchange data. The vision of the internet of things has evolved due to a convergence of multiple technologies, ranging from wireless communication to the Internet and from embedded systems to micro-electromechanical systems. The proliferation of these devices in a communicating–actuating network creates the Internet of Things (IoT), wherein sensors and actuators blend seamlessly with the environment around us, and the information is shared across platforms in order to develop a common operating picture. To realize the broad vision of pervasive computing, underpinned by the "Internet of Things" (IoT), it is essential to break down application and technology-based silos and support broad connectivity and data sharing; the cloud being a natural enabler. The key enabling technologies and application domains that are likely to drive IoT research in the near future are discussed. Our contribution is to analyze the current state of cloud-supported IoT to make explicit the security considerations that require further work.
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## 1. Introduction

The Internet has enabled an explosive growth of information sharing. With the advent of embedded and sensing technology, the number of smart devices including sensors, mobile phones, RF identifications (RFIDs), and smart grids has grown rapidly in recent years. Ericsson and Cisco predicted that 50 billion small embedded sensors and actuators will be connected to the Internet by 2020 forming a new Internet paradigm called Internet of Things (IoT). IoT can support a wide range of applications in different domains, such as health care, smart cities, pollution monitoring, transportation and logistics, factory process optimization, home safety and security.

This results in the generation of enormous amounts of data which have to be stored, processed and presented in a seamless, efficient, and easily interpretable form. This model will consist of services that are commodities and delivered in a manner similar to traditional commodities. Cloud computing can provide the virtual infrastructure for such utility computing which integrates monitoring devices, storage devices, analytics tools, visualization platforms and client delivery. In the past decade, many studies have contributed to the hardware, software, and protocol design of the smart devices, such as wireless sensor networks. Machine-to-machine automation with wireless sensors is being widely deployed, but usually in islands of disparate systems. The evolution of IoT attempts to connect these existing systems to the cloud, which enables advanced data fusion, storage, and coordination capability for achieving higher data quality and energy efficiency. The upcoming challenge of IoT lies in handling volumes of data generated from enormous amount of devices, which is known as the big data problem.

The wireless sensors in many IoT applications are battery powered, resulting in extreme energy constraints on their operations, such as sampling, data processing and radio communications.

However, for the Internet of Things vision to successfully emerge, the computing paradigm will need to go beyond traditional mobile computing scenarios that use smart phones and portables, and evolve into connecting everyday existing objects and embedding intelligence into our environment. For technology to disappear from the consciousness of the user, the Internet of Things demands: (1) a shared understanding of the situation of its users and their appliances, (2) software architectures and pervasive communication networks to process and convey the contextual information to where it is relevant, and (3) the analytics tools in the Internet of Things that aim for autonomous and smart behavior.

To conserve energy and achieve longer network lifetime, the costs of sensor sampling, processing, and radio communications have to be minimized. It is often the case that sensor readings in the same spatial regions are highly correlated. Depending on the application, the sensor readings are temporally correlated as well. By leveraging the computation capability of the cloud, data fusion can be performed to increase the data quality by exploring the spatial and temporal correlation of data. The wireless sensors can be coordinated by the cloud to be ON and OFF according to the change in the environment. In this paper, we explore a seamless solution by integrating cloud and IoT to provide comprehensive data fusion and coordination of sensors to improve data quality and reduce energy consumption.

Belief propagation (BP) is a technique for solving inference problems. In the IoT context, the belief of a sensor node is the data measurement of an event in the environment, and BP provides an iterative algorithm (also called the sum product algorithm) to infer the measurements of the sensor nodes, especially in cases where the data are missing, because of packet losses or because there are no data available at some selectively disabled sensor nodes (mainly to conserve energy and reduce radio inference). In BP, each sensor node determines its belief by incorporating its local measurement with the beliefs of its neighbor sensor nodes (spatial cooperation), and its beliefs obtained in the past (temporal cooperation). In such inference problems, the assumption that the data are spatiotemporally correlated significantly improves the accuracy of data inference using BP in WSNs.

This paper presents the current trends in IoT research propelled by applications and the need for convergence in several interdisciplinary technologies. In monitoring applications for the IoT, the data are collected and put in an environment matrix (EM), where the data readings for each sensor node are stored in one row of the matrix and each column index represents a timestamp for the interval at which the data were sampled. Hence, an EM is a matrix of size $N \times T$ where N is the number of sensor nodes and T the number of time intervals, and the time dimension T is expanding as more data are collected. BP performs the inference iteratively from the stream of data that are stored in EM based on the current and past data. Therefore, unlike the compressed sensing (CS) approach, BP does not require a complete EM for the whole duration of the time interval to perform inference.

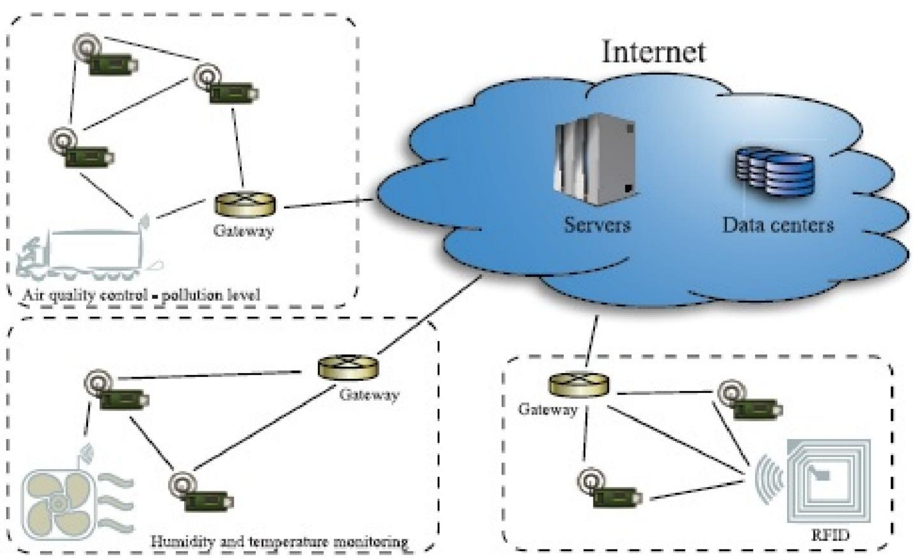


Fig. 1. Network architecture in an IoT

In this paper, we explore cloud-assisted adaptive sensing and data fusion to reduce energy consumption and improve data quality for the IoT. We propose an adaptive sensing BP protocol (ASBP), where the data are collected in several rounds (a round is a fixed time interval where the network repeats the same behavior) by active sensors (sensors that are collecting data in each round). We formulate and solve an optimization problem that selects the active sensors in each round, by maximizing the data utility while maintaining energy load balancing. We define data utility as the sum of the qualities of the path links from the selected active sensor nodes to the base station, subtracted by the sum of the correlations of the selected active sensors.

The creation of the Internet has marked a foremost milestone towards achieving ubicomp's vision which enables individual devices to communicate with any other device in the world. The inter-networking reveals the potential of a seemingly endless amount of distributed computing resources and storage owned by various owners. If the selected active sensor nodes are located on a path with greater link quality, then the value of the data utility increases. Likewise, if the selected active sensor nodes result in a lower data correlation, then the data utility is increased. In each round of ASBP, the minimum number of selected active sensor nodes (which is a parameter of our sensor selection optimization problem) is adaptively tuned based on the performance of the BP inference (data prediction accuracy) throughout the previous round. In addition to BP, we also use data quantization to further compress the data and reduce the transmission costs.

The advancements and convergence of micro-electro-mechanical systems (MEMS) technology, wireless communications, and digital electronics has resulted in the development of miniature devices having the ability to sense, compute, and communicate wirelessly in short distances. These miniature devices called nodes interconnect to form a wireless sensor networks (WSN) and find wide ranging applications in environmental monitoring, infrastructure monitoring, traffic monitoring, retail, etc. In our active sensor selection formulation, we consider nonlinear multihop routing protocol constraints. To model the sensor selection problem effectively, we use both constraint programming (CP) and heuristic-based greedy algorithm.

To take full advantage of the available Internet technology, there is a need to deploy large-scale, platform-independent, wireless sensor network infrastructure that includes data management and processing, actuation and analytics. Cloud computing promises high reliability, scalability and autonomy to provide ubiquitous access, dynamic resource discovery and composability required for the next generation Internet of Things applications. Consumers will be able to choose the service level by changing the Quality of Service parameters.

CP is a powerful framework to model and solve combinatorial problems. A CP model consists of variables, variable domains, and constraints, as well as objective function (if required), in which the constraints express the relation between the variables.


Fig. 2. Internet of Things schematic

Integrated IoT and Cloud computing applications enabling the creation of smart environments such as Smart Cities need to be able to (a) combine services offered by multiple stakeholders scale to support a large number of users in a reliable and decentralized manner. They need to be able operate in both wired and wireless network environments and deal with constraints such as access devices or data sources with limited power and unreliable connectivity. The Cloud application platforms need to be enhanced to support (a) the rapid creation of applications by providing domain specific programming tools and environments and (b) seamless execution of applications harnessing capabilities of multiple dynamic and heterogeneous resources to meet quality of service requirements of diverse users.

The core concept in CP is constraint propagation. Constraint propagation performs reasoning on a subset of variables, variable domains, and constraints to infer more restrictive variable domains, such that the restricted domains still contain all solutions to the problem. CP combines constraint propagation with search procedure to find a local or global optimum (using branch-and-bound search space exploration) to an optimization problem.

The contributions of this paper are as follows.

1) We present a novel data collection scheme (ASBP) that utilizes highly correlated spatio-temporal data in the network and uses BP to reconstruct the missing data due to packet losses and the sensor selection strategy.

2) We formulate the active sensor selection optimization problem, and propose two approaches, namely CP and a heuristic-based greedy algorithm to solve the problem. The CP approach solves the problem to optimality.

3) We conduct extensive simulation with a real deployment of a sensor network and the collected data to evaluate the impact of our proposed solution (for both CP and heuristic-based algorithm) on the overall energy consumption, data utility, and accuracy (error prediction of the missing data).

Internet of Things can be realized in three paradigms—internet-oriented (middleware), things oriented (sensors) and semantic-oriented (knowledge). Although this type of delineation is required due to the interdisciplinary nature of the subject, the usefulness of IoT can be unleashed only in an application domain where the three paradigms intersect.

**Literature Review**

The information industry benefits greatly from the technological advancements brought by the IoT. The IoT creates a bridge between many available and recent technologies, such as WSNs, cloud computing, and information sensing. In monitoring and data acquisition IoT-based systems, it is necessary to collect data effectively and efficiently. The IoT provides a platform for WSNs to connect to Internet and benefit from the power of cloud computing and data fusion. Therefore, it is necessary to study data collection schemes that can seamlessly integrate with the cloud and IoT systems. Data collection has been widely studied for stationary WSNs. Gnawali et al. present the stateof- the-art routing protocol for a sensor network where the nodes are forwarding data directly to a sink. They consider stationary WSNs that have static routes from the wireless sensors to the sink. Madden et al. introduced a distributed query processing paradigm called acquisitional query processing (ACQP) for sensor network data collection. The goal was to ensure a flexible tasking of motes via a relational query interface, while providing lifetime constraints, data prioritisation, event batching, and rate adaptation.

Prediction-based energy-efficient approaches aim at predicting the data to minimize the number of transmissions. Chou et al. proposed a distributed compression based on source coding, which highly relies on the correlation of the data, and it compresses the sensor readings with respect to the sensor past readings, and the reading measured by the other sensor nodes. They used adaptive prediction to track the correlation of the data, which is used to estimate the number of bits needed in source coding for data compression. Recent work in WSN addressed the use of compressive sensing. The authors use compressive sensing to exploit the temporal stability, spatial correlation, and the low-rank structure of the EM. They propose an environmental space–time-improved compressive sensing (ESTI-CS) algorithm to improve the missing data estimation. Although compressive sensing achieved good accuracy on the estimation of the missing data, it does only consider implicit spatio-temporal correlation in the data.

In our definition, we make the definition more user centric and do not restrict it to any standard communication protocol. This will allow long-lasting applications to be developed and deployed using the available state-of-the-art protocols at any given point in time. Our definition of the Internet of Things for smart environments is Interconnection of sensing and actuating devices providing the ability to share information across platforms through a unified framework, developing a common operating picture for enabling innovative applications. This is achieved by seamless ubiquitous sensing, data analytics and information representation with Cloud computing as the unifying framework.

Furthermore, compressive sensing approaches rely on the construction of a data matrix and thus require the synchronization of the sensors on the data collection. However, in our work, we present a BP approach for the prediction of missing data, where the spatio-temporal correlation is explicitly enforced and the inference is performed online and iteratively as the data are received at the base station. In addition to the above, to the best of our knowledge, there has been no work addressing a CP approach for energy-efficient sensor selection with dynamic routing, while considering the link quality and correlation of the data.

**Network Model**

In our IoT application, stationary sensor nodes collect environmental data, such as temperature, humidity, light intensity, and noise level. The network architecture of our data collection in IoT applications. We support heterogenous networks, where data can be collected from various devices. The network supports multihop routing and the gateways collect the data and forward the data to the cloud, where the data fusion is performed to further analyze the data, predict missing data, and store the data in the data centers. The computation power of the servers in the cloud is used to improve data quality and save energy of the sensor nodes using our ASBP protocol (to be discussed further in Section III-B). The sensor nodes periodically sample data, which is forwarded to the cloud using a multihop routing protocol. In this work, we use the real data collected at the Intel Berkeley Research Lab. The link thickness between the sensor nodes represents the value of the link quality aggregated throughout the experiment.

The data are collected at the cloud using the gateways associated with different applications of IoT. The gateway only relays the data to the servers in the cloud, and it is at least aware of the routing tables of the sensor nodes. In this paper, we refer to the gateway and the base station as the same entity; however, the actual computations (the CP solver and greedy algorithm are performed on the cloud, and all coordination are relayed by the gateway.

In our setup, the sensor nodes collect and report the data periodically (typically every 30 s). Our protocol operates in several rounds (a round is a time interval where the network repeats the same behavior), and each round includes two phases. The first phase is used to collect the minimum required information, which is used in the second phase to improve energy-efficiency, energy load balancing, and the data quality.

**Data Quantization**

Quantization is a classic technique in signal processing that has been widely used for data compression. Quantization of network data saves storage as it encodes the data into fewer bits. It requires fewer number of transmissions and smaller packet size. In many applications, a quantized measure is informative enough to represent aspects of the network.

The ability to uniquely identify ‘Things’ is critical for the success of IoT. This will not only allow us to uniquely identify billions of devices but also to control remote devices through the Internet. The few most critical features of creating a unique address are: uniqueness, reliability, persistence and scalability.

For example, many heating, ventilation, and air conditioning (HVAC) sensors only react if temperature or humidity falls within certain thresholds. In summary, quantized measures are less fine-grained and lossy; however, there are many advantages in using a quantized measure.

1) A quantized measure is informative enough for describing the correlation between the data.

2) A quantized measure can be encoded into a few bits, saving storage and transmission costs.

3) A quantized measure is coarse and thus cheaper to obtain. It is also stable and highly adjustable to match the needs of the network application.

Every element that is already connected and those that are going to be connected, must be identified by their unique identification, location and functionalities. The current IPv4 may support to an extent where a group of cohabiting sensor devices can be identified geographically, but not individually. The Internet Mobility attributes in the IPV6 may alleviate some of the device identification problems; however, the heterogeneous nature of wireless nodes, variable data types, concurrent operations and confluence of data from devices exacerbates the problem further.

On the inference accuracy, we compared our BP-based approach with the CS-based approach. In particular, modeled the estimation of the lost data as a problem of matrix completion, where an EM matrix is constructed by recording the data reading of a particular sensor at a particular time. The EM matrix is incomplete because some data are lost during transmission and some sensors are inactive, i.e., not selected, during some time periods. By applying the matrix completion techniques developed in CS, the missing data in the EM matrix can also be estimated. While interesting, a drawback of the matrix completion formulation is that in order to construct, data must be collected in different sensors regularly and in a synchronized way, so that the data in the time dimension are consistent. In contrast, our BP-based approach makes no such assumption and allows the sensors to collect data at irregular frequencies or even randomly. This is possible due to the explicit modeling of the data correlations in time and in space in the potential functions.

The data have to be stored and used intelligently for smart monitoring and actuation. It is important to develop artificial intelligence algorithms which could be centralized or distributed based on the need. Novel fusion algorithms need to be developed to make sense of the data collected. State-of-the-art non-linear, temporal machine learning methods based on evolutionary algorithms, genetic algorithms, neural networks, and other artificial intelligence techniques are necessary to achieve automated decision making. These systems show characteristics such as interoperability, integration and adaptive communications.

Developing IoT applications using low-level Cloud programming models and interfaces such as Thread and MapReduce models is complex. To overcome this, we need an IoT application specific framework for rapid creation of applications and their deployment on Cloud infrastructures.

The Dynamic Resource Provisioning component implements the logic for provisioning and managing virtualized resources in the private and public cloud computing environments based on the resource requirements as directed by the application scheduler. This is achieved by dynamically negotiating with the Cloud Infrastructure as a Service (IaaS) providers for the right kind of resource for a certain time and cost by taking into account the past execution history of applications and budget availability. This decision is made at runtime, when SaaS applications continuously send requests to the Aneka cloud platform.

The proposed Cloud centric vision comprises a flexible and open architecture that is user centric and enables different players to interact in the IoT framework. It allows interaction in a manner suitable for their own requirements, rather than the IoT being thrust upon them. In this way, the framework includes provisions to meet different requirements for data ownership, security, privacy, and sharing of information.

**Conclusion:**

By exploring cloud computing with the IoT, we present a cloud-based solution that takes into account the link quality and spatio-temporal correlation of data to minimize energy consumption by selecting sensors for sampling and relaying data. We have presented a novel cloud-based ASBP protocol with energy-efficient data collection for the IoT applications. ASBP solves an optimisation problem to select an optimal set of active sensor nodes that maximizes the data utility and achieves energy load balancing. In our protocol, BP iteratively infers the values of the missing data from the stream of active sensor readings. We have also compared our BP prediction results with the widely used compressive sensing technique, and show that our BP algorithm significantly outperforms compressive sensing. We formulate and solve the active sensor selection optimization problem using CP, and compare it with our heuristic-based greedy algorithm. We have evaluated the performance of our ASBP protocol by extensive simulations using real data collected at the Intel Berkeley Research Lab sensor deployment and their link quality estimates. The simulation results show that our ASBP protocol can greatly improve energy-efficiency up to 80%, with the optimal CP active sensor selection, while maintaining in average 5% error in the BP data inference.

As future work, we plan to extend our ASBP protocol to a fully distributed implementation for real deployment, and compare versus our current optimal results. We are also interested to integrate adaptive sampling rate into our current results, as well as investigating multisink scenarios.

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