Localizing Analytics

for Speed, Reliability and Reduced Power Consumption

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***Abstract* --- New tools make possible physics-based analytics in an embedded environment. By computing locally – performing predictive and prescriptive analytics at the edge of the IoT – significantly less data must be directed to the cloud. Further, the data sent are more informative and they are available in server-less situations. This improves reliability, speeds computation time and reduces power consumption. In addition, physics-based models have the ability to assess the internal state of an observed system. This makes their predictions more accurate. By enabling physics-based models to operate in real time in small footprint embedded devices, the resultant robust predictive ability can lead to a reduction of needed, and often expensive, system monitoring sensors. To illustrate how embedded model-driven analytics can be implemented, two real world examples will be demonstrated: an electric motor health monitor and a high voltage safety system. Each step in the implementation process will be shown, from model design to the utilization of embedded scientific computing tools, final real-time model optimization, and system predictions.**

Keywords --- analytics; physical analytics; Edge of the IoT; model-based analytics

I. Introduction

The vast amount of data generated by Internet of Things (IoT) devices and sensors is threatening with disrupting the current internet infrastructure. The prospect of billions of interconnected devices and sensors generating ceaselessly data creates unsustainable requirements in storage, energy and bandwidth. Just Machine to Machine (M2M) traffic is growing at a 49% CAGR according to CISCO, projected to be generating 14 exabytes/month up from 3 exabytes/month experienced in 2017[1]. To have a measure of comparison, one Exabyte is10^{18} bytes and some educated guesses about the storage capacity of Google place it somewhere around 10-15 Exabytes of data [2]. Industry, academia and even governments are becoming aware and investigate multiple approaches to address the impending very big data crisis [3],[4]. It is beyond the scope of this paper to delve in depth in all aspects of the problem. Instead we will focus on the role of analytics in reducing the traffic between IoT devices and the cloud.

II. The Role of IoT Analytics

All these IoT generated data can be valuable but only if they are interpreted in a useful way. This is the role of analytics –

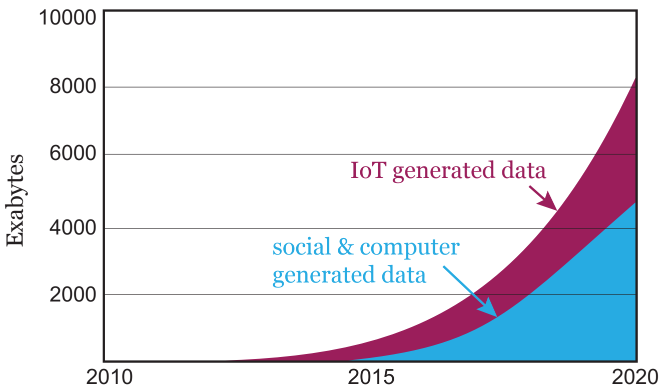

Figure 1: IoT generated data is growing faster than social & computer generated data

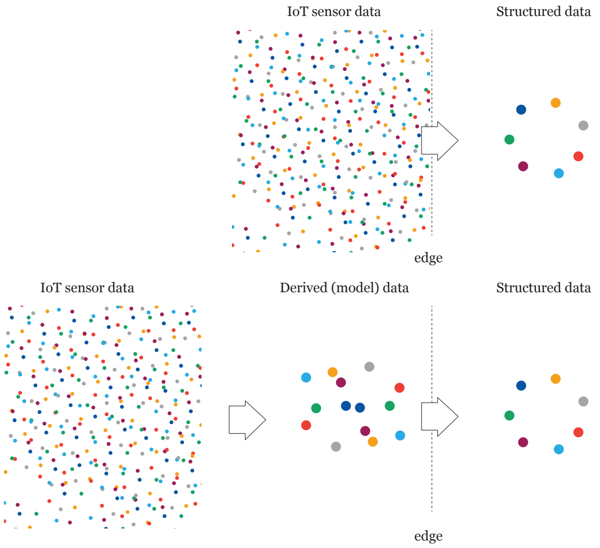

Figure 2: Performing analytics at the edge reduces storage, energy and bandwidth requirements

one of the most important applications in the IoT, which can be categorized as predictive and prescriptive analytics.

Predictive analytics aims to identify potential issues before they occur. The benefits are immediate; for example, unscheduled down time in a production line can be significantly reduced or eliminated.

Prescriptive analytics goes one step further by acting on the data through a feedback system that optimizes a process.

Given the storage, energy and bandwidth concerns that the very big IoT data is creating, it is optimal to perform the data analysis as close as possible to their source. Edge performed prescriptive analytics provide an added benefit by enabling local operational functionality during scheduled or unscheduled server-less conditions.

III. The Power of Physics in IoT Analytics

Big data generated by IoT devices and sensors are different than data created by social networks, financial or business transactions. Most analytics in the latter category are statistical, dealing for example with frequency of appearance of keywords or with relating healthcare protocols to patient outcomes. In contrast, data generated by IoT sensors are measurements of natural or man-made physical systems (e.g., temperature of a specific location or velocity of a motor shaft).

These physical systems are by nature deterministic, and their analysis traditionally has been physics-based. The purpose of phsysical systems analytics is primarily to extract information about the internal state of an observed system. Measurements are often limited to the observable behavior of the system. What we are interested though, in most of the cases, is the hidden information behind these data, which is, the internal state of the system. For example, we can measure the surface temperature of a battery but what we may be interested in is its core temperature which we cannot measure directly.

The association between the observables and the hidden state information is accomplished best through physics-based and mathematical models which by design relate the inputs to the outputs through a description of the system's internal dynamics. Physics models once they are derived do not change and they are data independent. If they contain enough details, at least in theory, they can predict accurately the response of an observed system to changing input conditions. So in theory if there is a physical model and we know its inputs we could

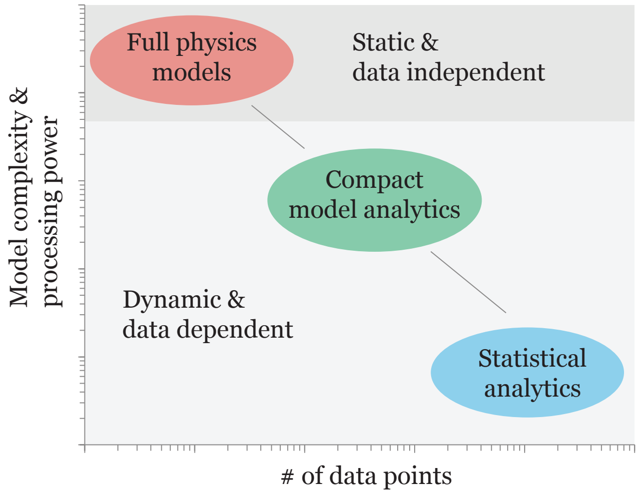

Figure 4: IoT physics based analytics lies between traditional physics models and big data analytics

predict its outputs. In practice, most physical systems are too complicated for accurately solving them within the time and computing resources available. In addition, there are physical phenomena that we do not completely understand, or they are too complicated to model. Finally, the real world observable data are noisy. These are some of the issues that IoT physical analytics can address.

In the IoT world observed physical systems reside in the analogous of a continuous experiment. As in traditional science experimenting manifests the dynamic process of knowledge advancement, similarly the co-existence of physics models and big data can create dynamic data dependent models with predictive power that can potentially provide better physical insights and advance knowledge. The mixing of physical models and experimental data is not novel. It has been used extensively in the semiconductor and other industries for the creation of *compact physical models*. In these models physics laws are combined with experimentally derived parameters and relationships in order to create small, fast and accurate model units that can scale well in very large simulations. In the big data IoT this combination of physics based models and experimental data can occur dynamically.

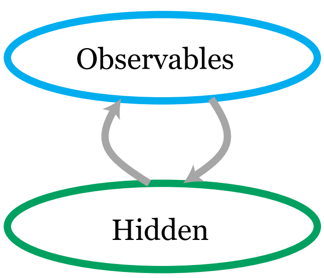

Figure 3: Physical systems analysis relates the observables with the hidden states

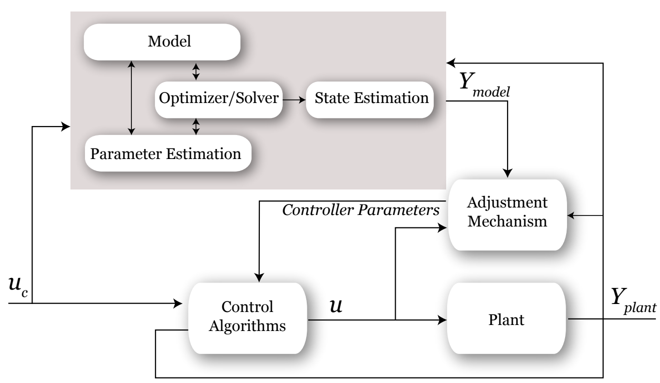

Figure 5: The model reads the inputs of the plant uc and predicts the output Ymodel. After comparison of its predictions with the actual outputs Yplant , it subsequently adjusts its parameters for a more accurate estimation of the current plant state

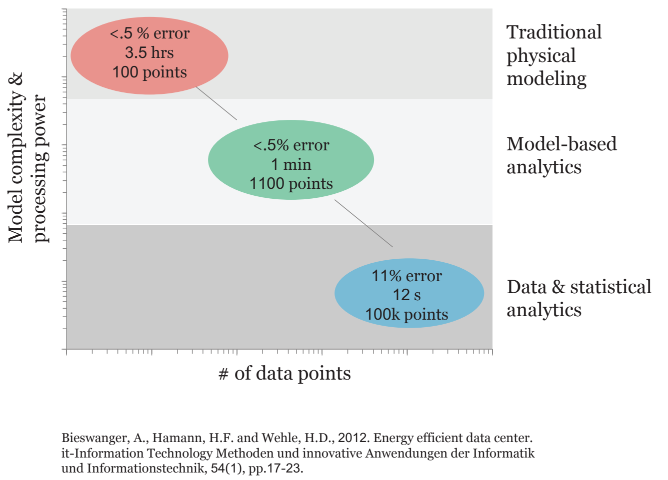

Figure 6: Model-based analytics can reduce processing time by utilizing a moderate amount of data.

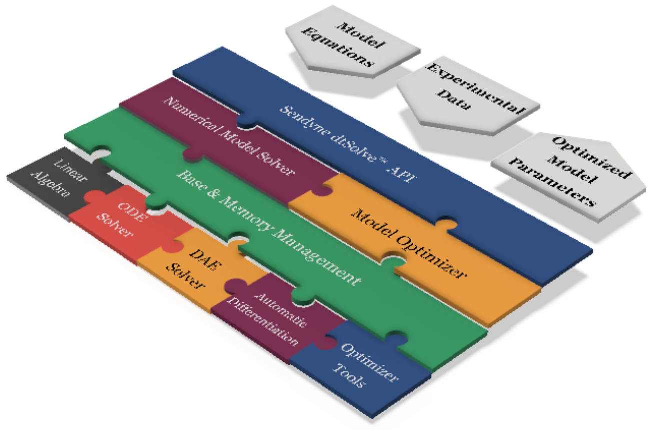

Figure 7: dtSolve is a state-of-the-Art numerical model solver and optimizer for embedded scientific calculation

IV. The Bridge Between Physical Models and Big Data

Physical model based analytics combines a model with real time measurements to derive an accurate estimate of a system's state. Using the same model it can also provide predictions for its future state based on different input scenarios.

Fig. 5 shows a typical implementation of the method as it is used in model predictive control. The model is sensing the same inputs and outputs as the observed physical system. The model compares its output predictions with the observed ones and dynamically adjusts its parameters in order to minimize the prediction error.

The model in this case acts as a consumer of sensor data utilizing them for its own optimization. Information that needs to be communicated, regards the system's state. Usually this information is much more compact, and it typically needs to be communicated less frequently than sensor generated data. What is needed is the model, typically described by means of differential equations and a suite of numerical tools that can solve the model and dynamically optimize its parameters.

To demonstrate the effectiveness of physical analytics in the IoT, IBM published estimates of RMS error calculations regarding the energy efficiency of a data center performed in three different ways. The results are shown in Fig. 6.

V. An IoT Platform for Edge Physical Analytics

There are two requirements for performing these functions at the edge. The first is sufficient MCU resources (such as the presence of a floating-point unit, amount of ROM and RAM memory). This power today exists in a variety of low cost MCUs.

The second is the availability of numerical tools that can solve and optimize physics based models described by a system of differential algebraic equations. These tools should be able to execute within the memory constraints of low cost MCUs, perform faster than the typical time scale of the modeled system as they are required to operate in real time, and be robust in the limited resource environments they operate.

dtSolve is a numerical package developed for this purpose. It consists of a numerical model solver and optimizer and a set of tools including an ODE and DAE solver, automatic differentiation, a linear algebra package and optimizer tools[5].

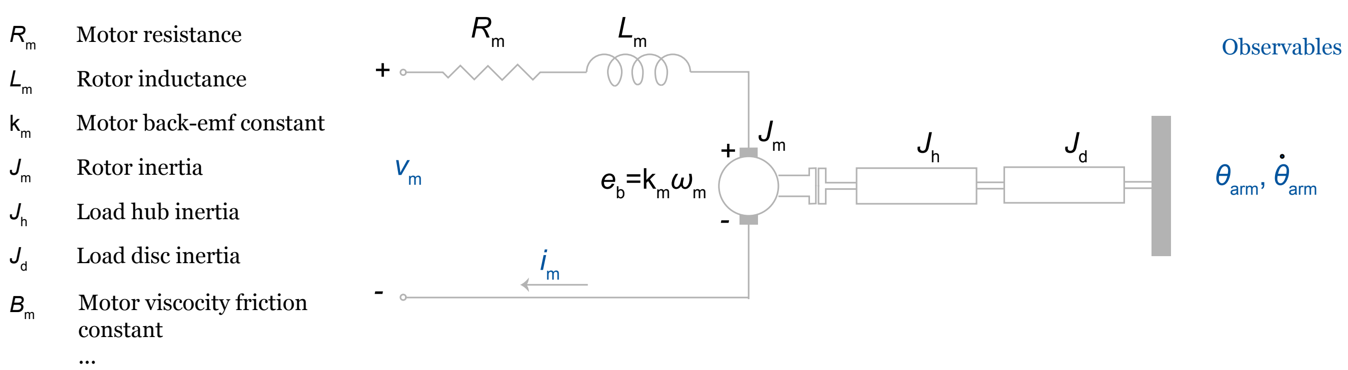

Figure 8: A simple model associating observables (in blue) with hidden information of interest for a DC motor system.

It occupies up to 300 KB of memory with all features enabled and benchmark testing against automatically-generated C code from Matlab Embedded Coder exhibits an order of magnitude faster execution and similar memory usage when solving the Van der Pol equations on an ARM Cortex-M4 MCU.

VI. Decentralized Scientific Processing

An example of how this technology can be deployed in the IoT is the monitoring of a factory floor. Multiple motors are operating generating a constant flow of voltage, current, rotor position, angular velocity and acceleration data. It is desirable to derive from these data through analytics the health condition of each motor in order to schedule maintenance and avoid unscheduled down time. Instead of transmitting all these data to a central processing location, a local MCU can utilize a model to associate the observed electrical and motion measurements with the device parameters of interest. Such a simple model is shown in Fig. 8 for a DC motor. Utilizing this model and measurement data the numerical solver and optimizer can fit the model parameters to the incoming data dynamically monitoring the health of the motor.

A typical scenario in this example would be to detect changes in the parameters describing the motor specifications and therefore detect the onsets of faulty behaviors: for example, changes in parameters related to friction and inertia of the shaft could indicate wear in the gear box, and changes in the motor inductance could indicate that the windings are deteriorating or overheating.

Moreover, within such a setup it would make sense to only transmit metrics related to the health condition of the system rather than the entire set of observed data. The rate at which the health condition metrics are transmitted can in turn be adapted to the health of the system itself: if the system is operating normally data can be transmitted at a slow rate, and if a faulty behavior is detected data can be transmitted at a higher rate so that the central processing location can accurately flag the system.

There are numerous other applications and methods that can benefit from the ability of fast and accurate scientific computing in small MCUs at the edge.

VII. Conlclusion

Decentralized scientific processing in the IoT provides a method for reducing the flow of sensor data by processing them right at the source. This IoT platform requires compact models and compact numerical solvers that can operate within today's MCU memory and speed constraints. Through physical analytics big IoT data can advance our understanding of the physical world and lead applications that turn big data in bigger returns.

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