Orchestrating the Cognitive Internet of Things

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Keywords: Internet of Things, CIoT, Smarter Planet, Behavior Models, Cognitive Computing, World Models, Smart Grid, DDDAS, Infosymbiotic Systems, Autonomy.

Abstract: The introduction of pervasive and ubiquitous instrumentation within Internet of Things (IoT) leads to unprecedented real-time visibility of the power grid, traffic, transportation, water, oil & gas. Interconnecting those distinct physical, people, and business worlds through ubiquitous instrumentation, even though still in its embryonic stage, has the potential to create intelligent IoT solutions that are much greener, more efficient, comfortable, and safer. An essential new direction to materialize this potential is to develop comprehensive models of such systems dynamically interacting with the instrumentation in a feed-back control loop. We describe here opportunities in applying cognitive computing on interconnected and instrumented worlds (CIoT) and call out the system-of-systems trend on interconnecting these distinct but interdependent worlds, and methods for advanced understanding, analysis, and real-time decision support capabilities with the accuracy of full-scale models.

1 INTRODUCTION

The rapid adoption of Internet of Things (IoT), together with unprecedented bandwidths and computational power in high-end, mid-range and instrumentation platforms and devices have already produced ground-breaking real-time visibility (or near real-time) access and transfer of information about a system or device in both natural and engineered systems, and in individual and industrial environemnts, such as in the following examples:

- personal condition (wearable devices, and smart phones),
- surrounding environment (bodycam),
- home (home security devices, appliances)
- power grid (eMeters, PMUs, other sensor and actuator in the power distribution systems)
- traffic and transportation (traffic sensors on cars, busses, trains, roads, traffic lights, railroads, aerial/UAVs, and congestion control devices)
- structural health monitoring (bridges, buildings, vehicles, aerial platforms)
- water systems (distribution grids, asset management and preventive maintenance; ambient environments)
- oil & gas (intelligent oil field)

Interconnecting those distinct physical, people, and business worlds (as shown in Fig. 1) through ubiquitous instrumentation, even though still in its embryonic stage, has the potential to unleash a planet that is much greener, more efficient, more comfortable, and safer. However, just a compedium and deluge of instrumentation data is insufficient in enabling these ultimate objectives. Cognitive representations (a.k.a. models) of these distinct physical, people, and business worlds are essential in understanding the complexity of these systems-of-systems worlds and their dynamics, and predicting and controlling their evolution, and creating accurate decision support capabilities when maneuvering through uncertain environments and not known a priori conditions. IoT combined with modeling is referred to as Cognitive IoT (CIoT).

Rich multi-fidelity and multimodal modeling and instrumentation are becoming key for enabling the above referenced capabiltiues for physical world systems (natural, engineered, and human systems). Beyond present notions of CIoT (Wu 2014, Zaidi 2015), new capabilties derived through modeling dynamically and synergistically integrated with instrumentation in a feed-back control loop are emerging (Darema 2000, 2005; Willcox 2014,

Li, C-S., Darema, F., Kantere, V. and Chang, V.
Orchestrating the Cognitive Internet of Things.
DOI: 10.5220/0005945700960101
In *Proceedings of the International Conference on Internet of Things and Big Data (IoTBD 2016)*, pages 96-101
ISBN: 978-989-758-183-0

Bazilevs 2012, 2013; Celik 2011, Son 2010). Furthermore, the trend towards higher fidelity, and (semi-)autonomy through humans in the loop is accelerating. Related methods and opportunities include fusing multiple world models to extract insights, capturing and using dynamic intelligent interactions, and orchestrating these interdependent models, information, processes, decisions, and actions. In addition, robust IT systems are essential for supporting the CIoT capabilities discussed above.

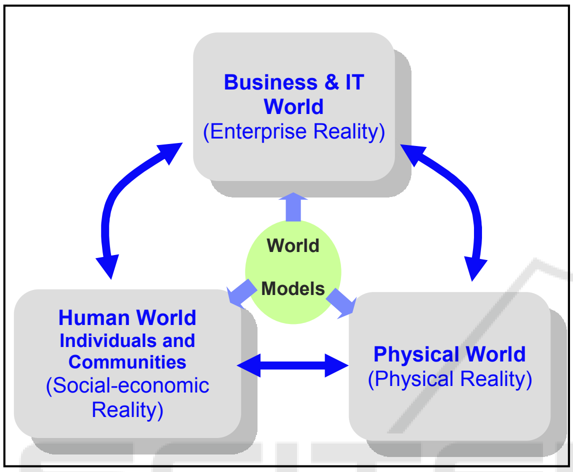

Figure 1: CIoT solutions will require interconnected and interdependent models representing the physical environment, business & IT, and individual & communities.

A cognitive Internet of Things (IoT) solution really is a feedback control loop system (or system of systems, since each individual component within this system could be a system by itself). Figure 2 shows the system view of such a closed-loop CIoT solution:

- Modeling & Orchestration Platform
- Data & Measurement Platform
- Control Platform

A CIoT solution inlcudes the real world itself – whether it is for example a smart grid, a smart building, a smart supply chain, or a smart water system; and the instrumentation provides mechanisms to capture information (of varying levels of fidelity) from the observed world to describe the real-world through models of the real world. As discuss more below, cognitive representations (or models) integrating data captured from the instrumented world enable interpolation or extrapolation of those areas where data could be noisy, unavailable, or contaminated. And in other cases, these models allow generation of the most plausible hypotheses to explain the available information.

From these models, the possible outcomes are generated through simulation and/or predictive analysis. Based on the what-if analysis conducted by the models, a course of actions is then taken to actuate the real world. This closed-loop system in reality is an instance of the closed-loop control system and is similar the MAPE loop of an autonomic system, with the exception that we will need to include the impacts from human (individually or as a community) to the system.

2 MODELS

A CIoT solution requires optimal or near optimal orchestration of the control flow and information flow. (*The music notes of the orchestration really came from behavior models which dynamically integrate real-world information*). Consequently, developing models at the behavior levels is necessary in order to enable optimal orchestration of both information and control flows. The behavioral models are continuously updated by the input data either to speed-up the execution by replacing parts of the computation in the model with the actual data or to impart additional information into the model as it is quite often that the model does not accurately or fully capture the system. The output of the behavior model controls the instrumentation in order to either refine data acquisition to improve the model accuracy or actuates the controllers to effect an action on the system or by the system (DDDAS/Infosymbiotics paradigm – Darema 2000, 2005, 2006, 2010). The kinds of models of interest

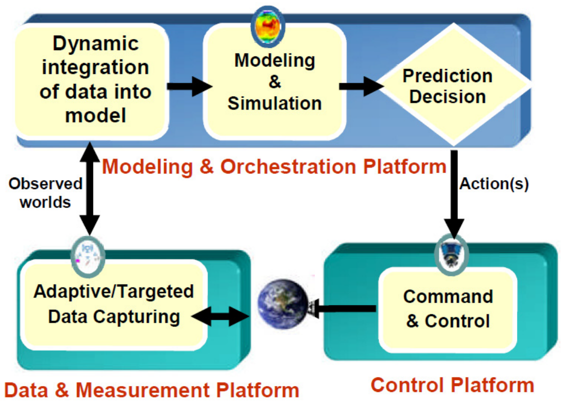

Figure 2: Interconnected platforms provide data dynamic capture & integration into models, orchestration of behavioral models, and control for closed-loop prediction & response.

span numeric and non-numeric, agent-based and graph models, as well as statistical models. Examples are given in Section 3.

There are multiple abstraction levels of models of the world. The most abstract level is at the conceptual (theory or functional) level. Additional details are available at the structural level. Behavioral level models often capture the most comprehensive aspects of the real world. Both at the structural and the behavioral level, there may be multiple levels of fidelity in describing the system at hand. The evolution of the abstraction levels of the model typically starts at the conceptual and/or functional levels. There are quite a few examples from various industries that demonstrate the gradual evolution of model sophistication, and examples are shown in Fig. 3.

During the development of Boeing 777, substantial portion of its dynamic behavior was entirely evaluated within a simulation environment rather than going through numerous wind-tunnel testing (Abarbanel 1996). In a later section, we discuss new and more powerful methods (DDDAS-based) that not only allow optimal design of aircraft, but also use new modeling methods (discussed in Section 2) to enable optimized operational capabilities under dynamic conditions.

Figure 3: Examples of multiple abstraction levels of models of the world.

Additional examples include the ability to simulate the IBM z10 chip entirely within the simulation environment in conjunction with virtual bring up and processor-only exercise. The ability of fully capturing the system at the behavior model level enables the first tape out and bring up of the IBM system z10 to be entirely successful (Lets 2009). Similarly, optimization in enterprise processes at the behavior levels saves multi-billion dollars annually through supply chain optimization (Min 2002; Son 2010).

The evolution from conceptual/functional models to behavior models in almost every domain in the past has improved business outcome with manageable complexity and uncertainty.

In general, the entire CIoT spectrum really includes physical worlds, business and IT worlds, and the human worlds, and can be further divided into at least six domains: physical, embedded (SCADA related), cyber, enterprise, community, and individuals.

During the past few decades, cognitive models in each of these silos are evolving from functional to structural and now to behavioral. In the foreseeable future, capturing and modeling the CIoT will happen at multiple abstraction, multiple resolutions and from multiple vantage points.

For example, in the enterprise domain, CBM (component business model) (Chesbrough 2010) and industry framework belong to the functional aspect. Industry models (including data models, process models, and service models) belong to the structural levels. Customer and workforce logistics and the enterprise risk models belong to the behavioral levels.

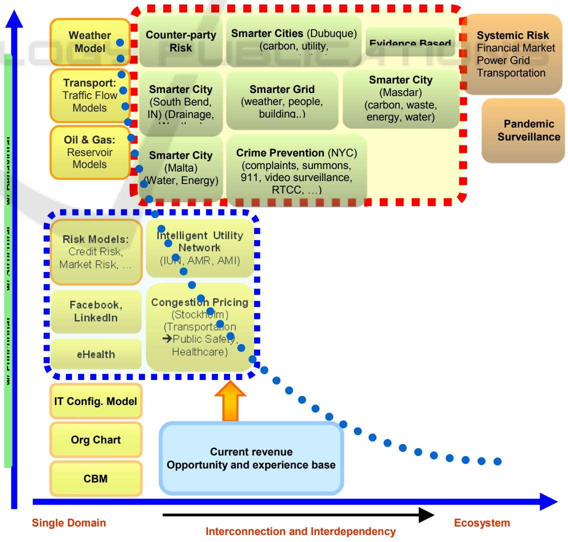

Figure 4: Future CIoT solutions will require interconnected and orchestrated measurements and models across multiple domains.

In the cyber area, ITIL (Canon 2011) can be viewed as belonging to the functional level while IT configuration model belong to the structural level and workload and network traffic belong to the behavior level.

For the community side of the human world, social networks (including LinkedIn and Facebook) capture the structural level of human relationship. Many of them evolve into capturing social or community behavior in real time. From the individual (personal) side, individual profile belongs to the functional level while the purchase history belongs to the behavior level.

The embedded system domain is related to electric grid, transportation, dam, traffic lights, and manufacturing where SCADA systems (Boyer, 2009) are often deployed. This area is transforming itself at an extremely fast pace as increasingly more of such systems are connected to each other as well as to the internet, and through DDDAS-based models.

By transforming from single domain into ecosystem, as in Fig. 4, we could gain new insight when analyzing the existing and future CIoT solutions. Many of the existing CIoT solutions fall into the category of single domain, and leveraging only structural models for static analysis. There are emerging opportunities – whether it is in the smart grid (power grid) or smarter city areas – often requires integrating more than one interdependent domain at the behavioral levels as well as DDDAS/Infosymbiotics based methods, of models dynamically integrated with instrumentation. There are advances and new capabilities that have been demonstrated along these directions (per examples in Section 3), and are likely ready to transition and be exploited by industry over the next 2-5 years.

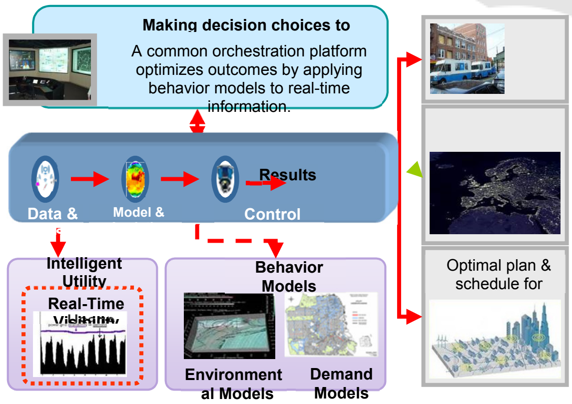

Figure 5: Smart Grid solutions continuously optimize the expected outcome dynamic data driven behavior models.

3 CASE STUDIES

In this section, we will use the smart grid and smart aerial platforms as examples to illustrate the behavior-model based orchestration in DDDAS-based CIoT solutions.

(A) Energy Related Applications

In a smart grid solution, intelligent utility networks (IUN) provide capabilities for real-time prediction of the onset of brown-outs or black-outs, and also provide optimized dynamic load management. The real-time instrumentation capability, often referred to as automatic meter reading (AMR) or automatic meter infrastructure (AMI), is based on measurements made by voltage amplitude phasor measurement unit (PMU) and other IoT sensors dynamically integrated with statistical and agent-based models. Dynamic load management within a Smart Grid solution includes activating mitigating actions prior to the onset of a brown-out or black-out to ensure differentiated support for critical and high-priority services vs. medium- and low-priority services for multiple customers and multiple (and possibly geographically dispersed) energy-sources (including renewables - such as wind, solar, and hydro, and energy storage which acts as a generation source) (Celik 2013, 2015).

Other scenarios include incorporating weather data and weather prediction models in dynamic data driven behavior models of the power-grid to provide continual optimization of load shedding during peak demand period (such as during summer) or restoration of the grid infrastructure after a weather induced failure (integrated outage management). Emerging scenario based on electric vehicles already led to a new demand class and potentially a generation source through the use of batteries. Furthermore, demand response management reduces demand during peak hours through incentives such as dynamic pricing plan.

With such capabilities, the utility companies will be able to provide much better assurance of the business outcome for their customers. The bottom line is to leverage the real-time visibility (instrumentation) in order to build real-time behavioral models so that the business can optimize the expected outcome continuously.

Other Smart Grid related areas such as wind farms pose new challenges and require new CIoT capabilities. These CIoT capabilities include optimized operation to mitigate effects of the wake across stacked turbines (Perez 2015) and reducing wear and tear or turbine rotors and prediction of an adaptive repair schedule rather than a static one (all turbines repaired periodically) (Ding 2006).

Accurate high resolution weather forecasts are central to predict potential storm severity and its path. IBM Research's Deep Thunder (Gallagher 2012) can provide high resolution forecasts for a 48 hour horizon for areas (in a given county) that are most likely to have outage events (with some uncertainty). This prediction can provide a basis for planning the deployment of repair crews and trucks in an anticipatory mode. An additional piece of analysis would be to schedule work orders and repair crews that would maximize the number of customers that are brought back online with each order. The ability to estimate the likelihood of damage in different regions allows for predictive planning in stationing crews for early repairs.

(B) Structural Health Monitoring, Energy Efficiencies, and Decision Support

Aerial platforms (both civilian and military, human-operated and UAVs, aerial and space-based) during flight are subject to dynamic stresses accentuated by turbulence-induced forces. Such stresses as well as aging of materials can result in structural damage, manifested as cracks, disbonding, delamination, or waviness. All these conditions can cause disastrous results with airplane crashing (as indeed have happened, such as aileron detachment). Additional sensor malfunction situations (such as pitot tubes freezing) also result in catastrophic failures. DDDAS-based modeling have shown advanced capabilities: (1) detection of the onset of damage (crack creation), (2) predict the propagation of the damage and potential impact (Willcox 2014), (3) application of time dependent control through coordination of multiple actuators to mitigate the propagation of the damage (Bazilevs 2012), and (4) wing-level and aerial structure-wide assessment of structure (5) through multi-fidelity models dynamically driven by multiple levels of sensors to assess platform health conditions in real-time, (6) cognizant of environment (such as winds and wind-induced turbulence) to plan and re-plan in real time to optimize flight path and necessary maneuver to fulfill mission (Willcox 2014, 2015). It was demonstrated in (Varela 2013, 2014) by using DDDAS-based methods to compensate for sensor failures. In this case, the output from a continually executing model of flight conditions is compared against the actual measurements from pitot sensor. The model can take over in case of abrupt discrepancy with the measurement to allow time to readjust and switch over to other sensor modalities .

4 SYSTEM IMPLICATIONS

CIoT solutions often have specialized requirements on processing through models the data derived from sensors and produce decisions and apply control through actuators. In some applications the value of data is highest when real-time or near real-time response was possible. In most applications both real-time and archival data are used as dynamic inputs into the models (e.g. weather, flight-path, etc). When multiple data sources are used as dynamic inputs into the behavior models, the value could be even higher as additional data can help to make the model more accurate, speed-up the model, reduce the uncertainty and contribute to the improved accuracy for predicting future condition and evolution of the system. In other applications, after the initial interval when the data contributes directly to the decision and proactive actions, the value of the data monotonically declines as the data can be potentially used for metering and billing, auditing, and long term trend analysis. As a result, system architectures optimized for CIoT solutions need to accommodate latency requirements and prioritize computation and communication resources in order to maximize the value that can be derived from the sensor data as well as the long term archive requirements to facilitate long term trend analysis.

Video surveillance is at the forefront of these requirements in terms of throughput (3.2-26GB/day/stream). SCADA systems and health monitoring systems have very stringent latency requirements (on the order of microseconds to milliseconds). High throughput and/or low latency requirements often mandate moving some cognitive capabilities to the edge of the CIoT solution even though the primary analytic functions are still carried out in the computing and data center(s).

5 ORCHESTRATION

Orchestrating a CIoT solution shown in Fig. 2 requires orchestrating interconnected platforms. These platforms include those capturing the information from the real world, dynamically integrating the information (measurement data) from the actual systems (the observed world) into the world model (including behavior models), for simulation and predictive analysis for what-if scenarios, and using the decision model (subject to the context and constraints) to render a set of command and control instructions that will yield optimal expected outcomes. These command and control instructions will then be executed by the command and control mechanisms and applied to the real world.

The modeling and analytic orchestration platform (the brain of a CIoT solution), coupling with the instrumentation (measurement and control). The lifecycle of analytics can start with the raw data coming from the real world, going through analytic environments that may include analysis engines for structured, unstructured, streaming, general analytics, application/algorithmic specific analytics, and dashboard/reporting tools, and in return additional raw data are collected, fed into the model to improve its accuracy or speed of the modeling. It's worth noting that when behavior models are tightly coupled with the data specific analytic environment, data modalities and very difficult to be generalized, and more general levels of abstraction of data and models are needed. Nevertheless, the DDDAS/Infosymbiotics paradigm provides a clear methodology of the value of dynamic integration of models and data in a feedback control loop.

6 CONCLUSIONS

The introduction of pervasive and ubiquitous instrumentation within a CIoT leads to unprecedented real-time visibility of the power grid, traffic, transportation, water, and oil & gas areas. Interconnecting those distinct physical, people, and business worlds through ubiquitous instrumentation, even though still in its embryonic stage, has the potential to unleash a planet that is much greener, more efficient, more comfortable, and safer.

In this paper, we described some of the opportunities after applying cognitive computing on interconnected and instrumented worlds and call out the system of systems trend on interconnecting these distinct but interdependent worlds. It has become increasingly crucial that cognitive representations of these distinct worlds (a.k.a. models, dynamically integrated with instrumentation) need to be created as a pre-requisite so in order to assess the complexity, maneuver through uncertain environments and eventually achieve the predicted outcome.

REFERENCES

Abarbanel, Bob, and William McNeely. "Flythru the boeing 777." ACM SIGGRAPH 96 Visual Proceedings: The art and interdisciplinary programs of SIGGRAPH'96. *ACM, 1996.*

Bazilevs, Yuri et al, "Toward a computational steering framework for large-scale composite structures based on continually and dynamically injected sensor data", *Procedia ComputerScience*, 9 (2012) 1149--1158.

Boyer, Stuart A. SCADA: supervisory control and data acquisition. *International Society of Automation, 2009.*

Cannon, David (2011). ITIL Service Strategy 2011 Edition. *The Stationery Office*.

Celik, Nurcin, et al. "DDDAMS-based Real-time Assessment and Control of Electric-Microgrids, *ICCS2011 Proceedings (2011).*

Chesbrough, Henry. "Business model innovation: opportunities and barriers." *Long range planning 43.2 (2010):* 354-363.

Darema, F., "Dynamic Data Driven Applications Systems (DDDAS)" NSF Workshop 2000, and 2006 and 2010 Workshopes (www.1dddas.org); " Dynamic Data Driven Applications Systems (DDDAS): New Capabilities for Application Simulations and Measurements", *ICCS05Proceedings (2005).*

Darema, F. , Grid Computing and Beyond: The Context of Dynamic Data Driven Applications Systems, *Proceedings of the IEEE, Special Issue on Grid Computing, March 2005 (invited paper).*

Ding, Yu, et al, "Dynamic Data-Driven Fault Diagnosis of Wind Turbine Systems" *ICCS2007 Proceedings (2007).*

Gallagher, Sean. "How IBM's Deep Thunder delivers hyper-local forecasts 3-1/2 days out." *Ars Technica (March 14, 2012).*

Hoffmann, C. et al "DDDAS For Autonomic Interconnected Systems: The National Energy Infrastructure", *ICCS2007 Proceedings (2007).*

Korobenko, A. Bazilevs, Y. et al"Structural Mechanics Modeling and FSI Simulation of Wind Turbines", *Mathematical Models and Methods in Applied Sciences*, 23 (2013) 249–272.

Letz, S., et al. "Functional verification of the IBM system z10 processor chipset." (2009).

McCalley James, et al "Integrated Decision Algorithms for Auto-Steered Electric Transmission System Asset Management", *ICCS2007 Proceedings (2007).*

Min, Hokey, and Gengui Zhou. "Supply chain modeling: past, present and future." *Computers & industrial engineering 43.1 (2002):* 231-249.

Son, Young Jun, et al, DDDAS-based Multi-fidelity Simulation Framework for Supply Chain Systems, *IIE Transactions on Operations Engineering, (2010),*

Willcox, Karen, et al " Multifidelity DDDAS Methods with Application to a Self-Aware Aerospace Vehicle, *ICCS2014 Proceedings (2014).*

Wu, Qihui. et al, "Cognitive Internet of Things: A New Paradigm beyond Connection", *Internet of Things Journal, V.1. IEEE (2014).*

Zaidi, Syed, et al, Cognitive Internet of Things: A Unified Perspective, *First International Internet of Things Summit(2014).*