Proceedings of the 2018 Winter Simulation Conference
M. Rabe, A.A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, eds.

DDDAS ADVANTAGES FROM HIGH-DIMENSIONAL SIMULATION

Erik Blasch

Air Force Office of Scientific Research
875 N. Randolph Street
Arlington, VA 22203, USA

ABSTRACT

Dynamic Data Driven Applications Systems (DDDAS) is a systems design framework that focuses on integrating high-dimensional physical model simulations, run-time measurements, statistical methods, and computation architectures. One of the foremost DDDAS successes was *scientific theory* assessment of natural disasters such as wild fire monitoring and volcanic plume detection. Monitoring the atmosphere with DDDAS principles has evolved into *domain methods* for space awareness, unmanned aerial vehicle (UAV) design, and biomedical applications. Recent efforts reflect the digital age of information management *architecture design* such as multimedia analysis, power grid control, and biohealth concerns. Underlying a majority of DDDAS developments are advances in sensor design, information filtering, and computational systems. The paper provides a motivation, explanation, and literature review of DDDAS.

1 INTRODUCTION

The paper captures the historical essence of the DDDAS literature. Invariably, the DDDAS paradigm was articulated by Dr. Darema who pioneered the concept (Darema 2005a; Aved et al. 2014): "*… instrumentation data and executing application models of these systems become a dynamic feedback control loop, whereby measurement data are dynamically incorporated into an executing model of the system in order to improve the accuracy of the model (or simulation), or to speed-up the simulation, and in reverse the executing application model controls the instrumentation process to guide the measurement process.*"

The DDDAS paradigm, and opportunities and challenges in exploiting the DDDAS methods, have been discussed in a series of workshops, starting in 2000 from the National Science Foundation (NSF). The reports from these workshops identified new science and technology capabilities, inspired by and enabled through the DDDAS paradigm. New capabilities include modeling approaches, algorithm developments, systems software, and instrumentation methods, as well as the need for synergistic multidisciplinary research among these areas (Darema 2005b). DDDAS brings together practitioners of application domains, researchers in mathematics, statistics, engineering, and computer sciences, as well as well as designers involved in the development of instrumentation systems and methods. Through a series of workshops, research efforts commenced to address the challenges and create new frontiers. As shown through the increasing body of work, DDDAS is applicable to many areas: such as (1) *engineering*: aerospace, biomedical, civil, electrical and mechanical engineering, (2) *systems*: manufacturing, transportation, and energy design, (3) *science*: environmental, weather, and climate science, as well as (4) *decision support*: medical diagnosis and treatment, multimedia analysis, and cyber security evaluation. This paper presents a summary of the DDDAS literature to motivate future developers interested in the DDDAS paradigm.

The rest of the paper describes the DDDAS paradigm. Section 2 discusses DDDAS control loops. Section 3 defines the DDDAS foundation in estimation and assimilation. Section 4 overviews DDDAS methods. Section 5 provides DDDAS historical literature review and Section 6 concludes the paper.

2 DYNAMIC DATA DRIVEN APPICATIONS SYSTEMS (DDDAS) CONTROL LOOPS

Consider an approaching hurricane. A meteorological model of the storm can be constructed, but this has limited predictive value without knowledge of initial conditions, boundary conditions, inputs, parameters, and states (such as velocities and accelerations). In order to make predictions, data is needed to estimate unknown quantities. Although the storm can be imaged at low resolution by satellite, measurements by aircraft with high resolution are expensive and limited in range, and therefore the size of the storm makes it impossible to obtain detailed measurements over a large area.

In such an approaching storm scenario, it may be possible to use the model to guide and reconfigure the sensors so that the information content of the data is enhanced for the ultimate objective of predicting the path and intensity of the hurricane. At the same time, the data collected by the sensors enhances the accuracy of the model by providing estimates of initial conditions, boundary conditions, inputs, parameters, and states. The integration of on-line data with the off-line model creates a positive feedback loop, where the model judiciously guides the sensor selection and data collection, from which the sensor data improves the accuracy of the model.

The hurricane example illustrates the essence of Dynamic Data-Driven Application Systems (DDDAS). DDDAS is a conceptual framework that synergistically combines models and data in order to facilitate the analysis and prediction of physical phenomena. In a broader context, DDDAS is a variation of adaptive state estimation that uses a *sensor reconfiguration loop* as shown in Figure 1 (Bernstein et al. 2015). This loop seeks to reconfigure the sensors in order to enhance the information content of the measurements. The sensor reconfiguration is guided by the simulation of the physical process. Consequently, the sensor reconfiguration is *dynamic*, and the overall process is *data driven*.

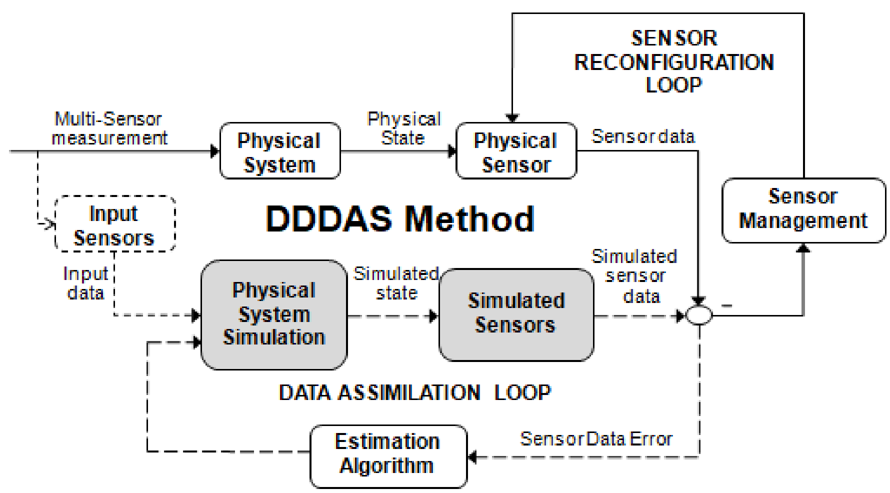

Figure 1:Dynamic Data-Driven Application Systems (DDDAS) feedback loop.

The core of DDDAS is the *data assimilation loop*, which uses sensor data error to drive the physical system simulation so that the trajectory of the simulation more closely follows the trajectory of the physical system. The data assimilation loop uses input data if input sensors are available. The innovative feature of DDDAS is the additional *sensor reconfiguration loop*, which guides the physical sensors in order to enhance the information content of the collected data. The data assimilation and sensor reconfiguration feedback loops are *computational* rather than physical feedback loops. The simulation guides the sensor reconfiguration and the collected data, and in turn, improves the accuracy of the physical system simulation. The "model-based simulated data" positive feedback loop is the essence of DDDAS. Key aspects of DDDAS include the algorithmic and statistical methods that incorporate the measurement data with that of the high-dimensional modeling and simulation.

3 STATE ESTIMATION AND DATA ASSIMILATION

The goal of *state estimation* is to combine models with data in order to estimate model states that are not directly measured. State estimation is a foundational area of research in systems and control. Relevant techniques date from the 1960's in the form of the Kalman filter and the Luenberger observer. An observer is a model that emulates the dynamics of a physical system and is driven by sensor data in order to approximate unmeasured states. The Kalman filter is a stochastically optimal observer that estimates unmeasured states. In large-scale physics applications, such as applications involving structures or fluids, state estimation is called *data assimilation*.

The Kalman filter (KF) was developed for linear systems. However, most real applications involve nonlinear dynamics, and the development of observers and filters for nonlinear systems is a challenging problem. Numerous techniques, which can be described as suboptimal, ad hoc, application-based, or approximate, have been developed, and many of these methods are widely used such as the extended Kalman filter (EKF), ensemble KF (EnKF), ensemble adjustment KF (EnAKF), unscented KF (UKF), stochastic integration filter (SIF), and particle filter (PF) (Yang et al. 2005;Dunik et al. 2015).

3.1 DDDAS and Adaptive State Estimation

State estimation algorithms are based on prior information about the physical system for data fusion (Blasch et al. 2012a). The information typically includes a physical system model as well as knowledge of the initial state, inputs (such as disturbances), and sensor noise. Likewise, a stochastic representation uses a statistical description of the disturbances and sensor noise. An adaptive state estimation algorithm may attempt to learn and update the information, states, and parameters online.

DDDAS uses adaptation in a different sense. In particular, DDDAS seeks to reconfigure the sensors during operation. Sensor reconfiguration, driven by the model, enhances the information content of the measurements. The sensor reconfiguration loop is shown in Figure 1. Together, the integration of the data assimilation loop and the sensor reconfiguration loop are central to methods using DDDAS.

3.2 Does DDDAS Use Feedback Control?

DDDAS uses computational feedback, but not physical feedback. As Figure 1 shows, state estimation is a *feedback process*, where the sensor error corrects the simulation of the physical system. The data assimilation feedback loop is implemented in computation, and thus has no effect on the physical system.

DDDAS employs an additional feedback loop by reconfiguring the sensors based on the sensor error data. The sensor reconfiguration feedback loop is also computational, and thus does not affect the response of the physical system. In contrast, feedback control uses physical inputs (such as forces and moments) in order to affect the behavior of a physical system, such as an aircraft autopilot that drives the control surfaces and modifies the aircraft trajectory. Consequently, DDDAS employs two computational feedback loops, *but does not only use physical feedback control*. The power of DDDAS is to use *simulated data from a high-dimensional model* to augment measurement systems for systems design to leverage statistical methods, simulation, and computation architectures.

4 DDDAS METHODS

The DDDAS framework, as it name implies, has been applied to many applications where modeling and data collection are utilized in engineering and scientific analysis. Hence, four methods of DDDAS include: (1) instrumentation methods (Virani et al. 2015), (2) statistical algorithms (Maroulas et al. 2015), (3) modeling and simulation (Chaturvedi 2006), and (4) systems software(Darema 2010), as shown in Figure 2. For DDDAS operations, the use of the model; along with updated measurements and operating conditions of the available sensors, targets, and the environment (Kahler et al. 2008); support the simulation. The model represents the key parameters, behaviors and functions of the selected physical system or abstract process. The model represents the system, while the simulation projects the system operation over time.

Instrumentation methods include multidomain components in real-world situations such as space sensors monitoring the atmosphere; avionics sensors detecting air movements, computer vision detecting vehicles on a terrain road network, as well as, water properties in the ocean. Complementing the application is *high-dimensional simulation models* such as the space Global ionosphere–thermosphere model (GITM) model, the National Climate Atmospheric Reference (NCAR) model, ground-based vehicle traffic models, and oceanic radar scatter models. Together the integration of the modeling and data collection requires *software systems* to process the large data sources and model parameters. The coordination of high-end with real-time computing requires new hardware and software approaches in the fields of optimization, data flow architectures, and data science to being together modeling and instrumentation methods for real world applications.

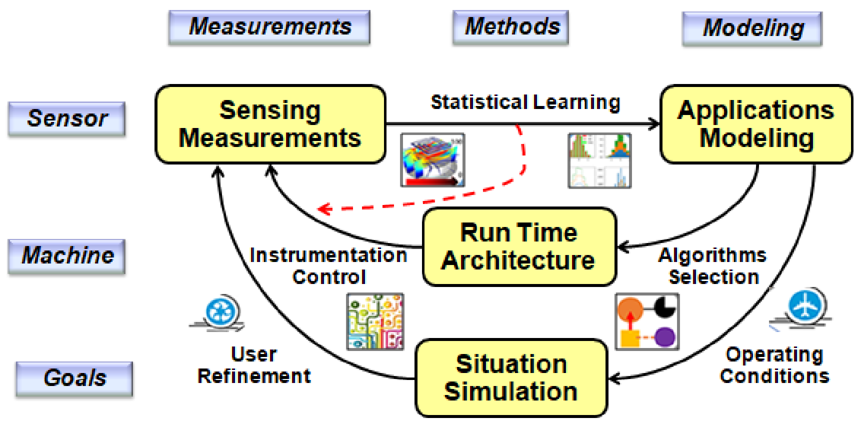

Figure 2: Dynamic Data-Driven Application Systems (DDDAS) Attributes.

Three examples are presented in Figure 3 which demonstrates DDDAS methods applied to enhance awareness. The examples are air, space, and cyber domains where instrumentation, modeling, and software have been designed for real platforms. On the left is weather modeling with nonlinear tracking methods for unmanned aerial vehicle (UAV) flight routing. The middle includes multi-domain robotics of space and ground vehicles with filtering methods for distributed autonomous coordinated control. Finally, the cyber example comes from power grids performance that integrates domains of cyber physical systems (CPS) with the internet of things (IoT).

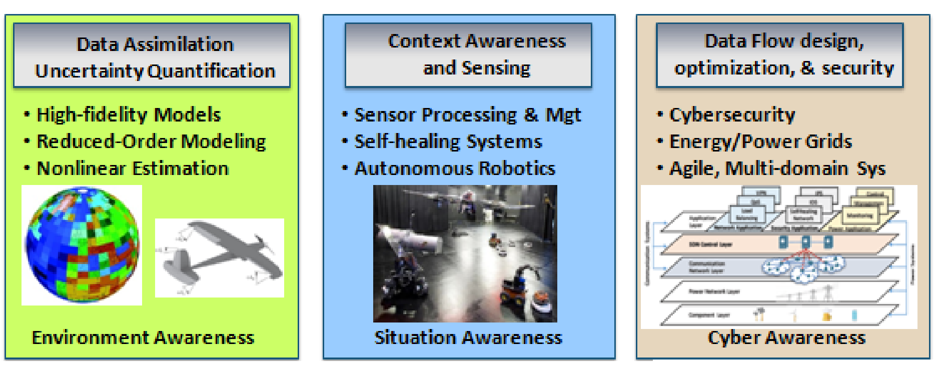

Figure 3: Dynamic Data-Driven Application Systems (DDDAS) Awareness Examples.

As briefly described, DDDAS is the integration of instrumentation, statistical processing and modeling methods (sensor reconfiguration loop); owing to the fact that not all data is observable and hence, there is a needed for simulation from high-dimensional models to augment systems awareness (data assimilation loop). The incorporation of simulated data for run-time applications requires pragmatic systems and software architectures. The literature review organization highlights a diverse set of applications inspired by the DDDAS concept from science to engineered systems.

5 DDDAS RESEARCH LITERATURE REVIEW

The concepts for DDDAS have developed for almost two decades starting with an initial NSF workshop in 2000 that brought together researchers, engineers, scientists and developers. The initial workshop focused on harnessing the power of theory, modeling, sensing, and hardware advances to instantiate systems-level opportunities. The growing interest in DDDAS is demonstrated in the literature, as shown in Figure 4. The statistics from Figure 4 only capture those papers that call out DDDAS as the underlying paradigm; while many other papers which have briefly acknowledged DDDAS are not included in Figure 4. There is a growing trend in approaches using DDDAS, which is established through the website.

Over the years, many researchers have embraced the DDDAS concept with a variety of simulated applications as shown in Figure 5 (Darema 2011). Areas of interest shown in the illustrations include data assimilation, UAV swarms, decision support, simulations, and wildfire analysis; among others. The next section organizes many of the papers in the last 20 years into the areas of theory, methods, and design.

Many forums have provided opportunities for showcasing advances in DDDAS. The primary meetings that highlighted the advances include: (1) *International Conference on Computational Science* (ICCS); (2) *IEEE Winter Simulation Conference* (WSC), (3) *IEEE American Controls Conference* (ACC); and (4) *International Conference on Information Fusion* (Fusion).

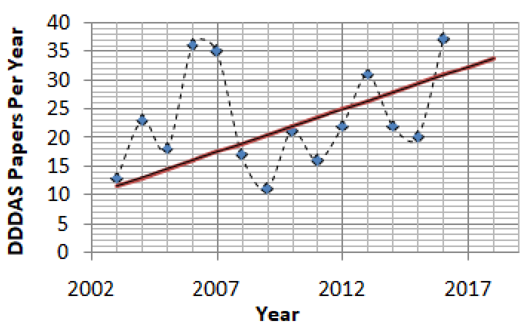

Figure 4: DDDAS papers per year.

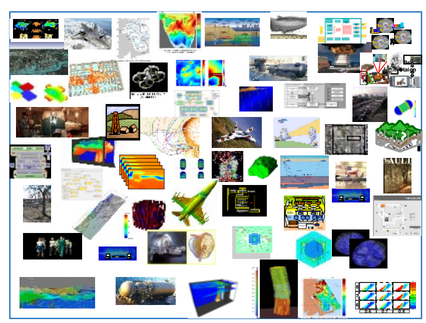

Figure 5: DDDAS results.

Along the way, there have been countless meetings and workshops such as the Dynamic Data-driven Environmental Systems Science Conference (DyDESS) (Ravela et al. 2014). DyDESS focused on scientific methods such as (1) Perspectives from Ocean State Estimation, (b) Imaging Earth's interior with active and passive source seismic data, (3) objective detection of Lagrangian vortices in unsteady velocity data, and (4) data assimilation and controls for atmospheric multiscale dimensional processing.

The history of DDDAS extends from two decades of developments. To organize the diverse set of literature, three areas include: (1) scientific theory, (2) domain methods, and (3) architecture designs. Key areas for *theory* are based in the scientific areas with large data collections and complex models. *Methods* include various engineering designs for various domains – space, air, and ground, requiring dynamic response and control. Finally, computational architectures focus on *systems design*. Given the diverse DDDAS literature, various taxonomies could be highlighted; however, the conclusions drawn from the survey review is that DDDAS has a wide-ranging applicability on the scientific, development, and design communities, as shown in the Table 1, that organizes the literature for the reader.

Table 1: Summary of DDDAS Literature Review*.

	Awareness	Monitoring	Data Fusion	Application
Scientific Theory	Weather Forecasting	Wildfire Monitoring	Ash Detection	Medical Support
Domain Method	Space Awareness	Structural Health	State Estimation	Self-Aware Vehicles
Architecture Design	Network Trust	Energy Analysis	Image Computing	Cyber-Physical Systems

**Valid reviewer concerns suggested a taxonomy of applications (e.g., space awareness), methods (e.g., KF), and models (e.g., GITM) as described previously; however, the diverse areas revealed specific theory, methods, and models for each application of the elements in the table.*

5.1 Scientific Theory – Modeling and Analysis

The DDDAS paradigm began with enhancing the phenomenology of *science models* such that measurement information would enhance the resulting model. In 2003, key attributes included measurement information, data assimilation, and adaptive sampling incorporated into multiphysics, ocean forecasting, and atmospheric modeling (Sandu et al. 2004).

As the DDDAS methods showed promise in science applications, a key area was in *weather forecasting* such as assessing tornado prediction (Trafalis et al. 2007). Simultaneously, DDDAS began addressing theoretical uncertainty and quantifying error minimization (Royet et al. 2007). Years later, Ravelaet al. (2012) and others began to use the information from weather forecasting (e.g., coherent fluid analysis) for advances in applications UAV controls, routing, and sensing (McCune et al. 2013).

Along with weather forecasting was another related application for *wildfire monitoring* such as agent-based simulations for fire propagation modeling (Michopoulos et al. 2004), which is still valid today. A set of researchers, lead by Coen, (Mandel et al. 2007), continued to use the DDDAS paradigm for inclusion of advanced physical models of wildfire prediction with that of real-time sensing. Within the CAWFE® (Coupled Atmosphere-Wildland Fire Environment) modeling system, various sensors such as the Visible Infrared Imaging Radiometer Suite (VIIRS), provided analysis of smoke plume detection in the United States. The wildfire assessment method was extended to other geographic locations such as Europe (Rodriguez-Aseretto et al. 2013). Furthermore, fire detection and mitigation sought to understand the management of water distribution (Wang et al. 2014).

A recent example is that of *volcanic ash detection* (Patraet al.2013). Atmospheric analysis can have impacts on commercial air transport, such as the recent eruption in Iceland. The particulates in the air from the eruption could have disastrous effects on combustion engines moving an aircraft through the sky. Likewise, with the detection of changes in the weather content, environmental wind context, and navigational data could be used to alter the air traffic management of the networked skies. Advances in uncertainty quantification were incorporated into the ash movement modeling so as to prepare aviation for future events and provide passenger safety. Uncertainty quantification helps in estimate error reduction in complex modeling and estimation methods (Rao et al. 2014).

Science applications also include areas for bio-sensing and analysis for *medical applications*. One example is using image recognition for tracking human responses to stress and expressions. Metaxas et al.(2004) developed DDDAS methods using image recognition and face tracking. Other examples include using the sensing to update models of humans in support of neurosurgery (Majumdar et al. 2005) and laser treatment of cancer. In each of these cases, DDDAS supported enhancements in medical treatment through advanced modeling. Further DDDAS developments include diagnostics, chemical treatment, and pandemics.

5.2 Domain Methods –Applications

Building upon the DDDAS principles for science applications influenced another area of development which moved from data assimilation analysis to that of control and filtering. As highlighted earlier, an extension of the scientific modeling of the air environment was to the atmosphere that extends to *space awareness*. Bernstein's research group (Kim et al. 2006) utilized the DDDAS principles for data assimilation using the global ionosphere-thermosphere model (GITM). While it was a scientific analysis, it moved the DDDAS community towards adaptive control and sensing. Simulations were conducted to determine the effects on planetary motion and movement of atmospheric elements (Morozov et al. 2013). A third example extends these developments for the Retrospective Cost Model Refinement (RCMR) that includes modeling, sensing and control (Burrell et al. 2015). The developments provide for advances in satellite protection, space-based sensing, and space awareness (Blasch et al. 2017).

Protection of platforms, such as satellites, is also a key area for DDAS including *structural health monitoring* (SHM). Farhat et al. (2006) utilized the DDDAS principles towards SHM of materials assessments of equipment. Having an accurate model, with embedding sensing, supports real time response to a dynamically changing environment. Additionally developments include reduced-order modeling (ROM) such that the ensemble of models can be refined over model parameters, uncertainty estimation, and sensing bias. Oden's research group provided additional benefits of SHM for damage assessment and others highlighted modeling updates that account for materials damage (Prudencio et al. 2015) which are useful for aerospace systems resiliency.

To achieve the efforts in analysis over multiple domains requires the data coordination and *estimation*. Using the ensemble Kalman filter, Sanduet al. (2004) addressed the computational aspects of data assimilation for aerosol in the atmosphere while Ravela et al. (2006) devised methods for air platform positioning. Other methods looked at the methods to use in forecasting (Jiaet al. 2016). If the DDDAS methods are able to forecast the movements, they can be use field alignment to estimate vehicle locations such as with quadrature information (Ravela et al. 2007). Likewise, the fidelity of the parameters affects the estimation of model accuracy (Henderson et al. 2013), which enables a mixture of ensembles (Tagade et al. 2014).

Estimation methods are elements of *data fusion* techniques (Zheng et al. 2018). The integration of measurements includes data, sensor, and information fusion aligns well with the DDDAS principles (Blasch 2013a). DDDAS improves automatic object recognition ((Blasch et al. 2012a, Blasch et al. 2013c) such as nonlinear classification of moving objects using signal and pixel data (Chin et al. 2015). Moving object analysis utilizes data fusion for ground vehicle tracking and multidimensional assignment of hyperspectral data to gather relevant features of the moving object (Uzkent et al. 2016).

Recently, Wilcox's group (Allaire et al. 2013) have utilized online/offline modeling in support of *self-aware vehicles* which paves the way for autonomous systems. Included in their research is a focus on the model dimensionality for operational performance. As a second example, Mohseni's research team (Peng et al. 2014) applying DDDAS for control and atmospheric sensing using air and water autonomous systems. The monitoring of the environment supported the health monitoring of the vehicles with a changing environment. These developments have been incorporated into the control of soaring vehicles (Frew et al. 2013). The third example includes onboard avionics to sense fault detection (Silva et al. 2015). Varela's group (Imai et al. 2017) has led a group to bring together computations with that of electronics health assessment for safe flight of self-aware vehicles using estimation techniques.

The DDDAS concept leverages models such as scene, roads, or other terrain information (Blasch 2013b). Context aware approaches were investigated (Nguyen et al. 2013), along with the need to learn the measurement models (Virani et al. 2015). These methods were furthered by the information fusion community for context-enhanced information fusion which shows how DDDAS techniques can improved tracking over many operating conditions for robust performance (Snidaro et al. 2016).Context enhancement solutions leverage theory and methods, but effective and efficient applications require architectural design.

5.3 Architecture Design – Systems and Software

The third section of the review includes systems architecture, energy networks, systems design, and cyber network analysis, with recent efforts in cloud computing (Liu et al. 2014). In the early DDDAS methods, there was a need for scalable *architectures* and agent-based systems where evaluated (Chaturvedi 2006). DDDAS showed promise for web-based methods provide a use case for distributed simulations for computer data streaming (Anderson et al. 2006). Web-based methods afford query languages for DDDAS designs (Aved et al. 2015) and analysis (Blasch, Phoha 2017).

The distributed aspects of network analysis were adapted and applied for power system and *energy analysis* (Abed et al. 2006; Celik et al. 2013). Power analysis as a function of microgrids can support the power and energy available for aircraft which requires an adequate model of the energy distribution (Frew et al. 2013). As for ground vehicles, the energy consumption can be improved both locally for a car and globally for traffic (Neal et al. 2016).

The networks, whether power grids or equipment, the effective global analysis can improve situation awareness for supply chains (Carnahan et al. 2006) and disaster management. The *systems approach* applied to smart cities and urban infrastructures supported assessment of emissions on the climate (Fujimoto et al. 2016). Likewise, with the systems analysis, methods can support the design of embedded electronics for signal processing (Sudusinghe et al. 2014). These methods were further analyzed for adaptive video stream processing (Chakravarthy et al. 2015; Li et al. 2017).

Recent trends have changed the network application to include *communication networks*. While traditionally DDDAS looked at these methods for web services, DDDAS revised trust monitoring on a network (Onolaja et al. 2010), such that trust and privacy relied on the trust analysis for sensing control and assignment (Pournajaf et al. 2014). Recent efforts include extending these and a comprehensive analysis of DDDAS and the coordination of trust was explored(Blasch et al. 2014; Badr et al. 2015).

Finally, the integration of DDDAS with cloud computing has shown promise for the advancement of *systems and software solutions*. Verification and validation (Michopoulos et al. 2006) and Quality of Service (QoS) optimization improved using DDDAS (Chen et al. 2013). The use of a cloud-based system was successful for real-time tracking of objects from Wide Area Motion Imagery (WAMI) streaming data (Wu et al. 2016). Another approach used cloud computing for cyber physical systems (CPS) to manage the data streams between CPS networked devices and those of sensors at the edge (Shekar et al. 2016). Li, Darema, and Chang (Li et al. 2017) combined these methods in a review of DDDAS support to a variety of applications such as distributed behavior model orchestration in cognitive internet of things (IoT).

6 CONCLUSIONS

Fundamental basic research in DDDAS is gathered from, and contributes to scientific applications, mathematical foundations, and infrastructure architectures. Specifically, DDDAS includes(1)*theory*(e.g., data assimilation, process modeling and filtering, and estimation); (2)*methods*(e.g., structural analysis for structural health monitoring, systems control for component processing, and image computing for situation evaluation); and (3)*design* (situation awareness through environmental assessment, energy aware power grids, and cyber awareness concerning privacy and security protections).

The DDDAS paradigm literature survey revealed these commonalities: (1) use of high-dimensional models to augment low-dimensional instrumentation systems such as weather models for real-time vehicle control, (2) broad applicability manifesting from advances in computation such as cloud computing for streaming content network analysis, and (3) alignment with data science trends including simulation for context awareness and systems monitoring. Future DDDAS-inspired methods would benefit from recent advances in machine learning, distributed computing, and network optimization.

ACKNOWLEDGMENTS

The author acknowledges discussions with Dr. Darema, Dennis Bernstein, Murali Rangaswamy, and Sai Ravela. The views and conclusions contained herein are those of the author and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the U.S. Government.

REFERENCES

Abed, E. H., N. S. Namachchivaya, T. J. Overbye, M. A. Pai, P. W. Sauer, andA. Sussman. 2006. "Data Driven Power System Operations". In *Proc. of the International Conference on Computational Science*, edited by V. N. Alexandrovet al.,448-455, Springer-Verlag.

Allaire, D., J. Chambers, R. Cowlagi, D. Kordonowy, M. Lecerf, L. Mainini, and K. Willcox. 2013. "A Baseline Offline/online DDDAS Capability for Self-aware Aerospace Vehicles". *Procedia Computer Science* 18:1959-1968.

Anderson, K. S., J. P. Bigus, E. Bouillet, P. Dube, N. Halim, Z. Liu, and D. Pendarkis. 2006. "SWORD: Scalable and Flexible workload generator for distributed data processing systems". In *Proc. of the 2006 Winter Simulation Conference,* edited by L. F. Perrone et al*.,* 2109-2116 Piscataway, New Jersey: IEEE.

Aved, A. J. and E. Blasch. 2014. Dynamic Data Driven Application Systems.www.1dddas.org, accessed August 21, 2018.

Aved, A. J. and E. Blasch. 2015. "Multi-INT Query Language for DDDAS Designs". *Procedia Computer Science*51:2518-2523.

Badr, Y., S. Hariri, Y. Al-Nashif, and E. Blasch. 2015. "Resilient and Trustworthy Dynamic Data-Driven Application Systems (DDDAS) Services for Crisis Management Environments". *Procedia Computer Science* 51:2623-2637.

Bernstein, D. S., A. Ridley, J. Cutler, and A. Cohn. 2015. "Transformative Advances in DDDAS with Application to Space Weather Monitoring". Project Report ADA623483.University of Michigan.

Blasch, E., E. Bosse, and D. A. Lambert. 2012a. *High-Level Information Fusion Management and Systems Design*. Norwood, MA: Artech House.

Blasch, E., G. Seetharaman, K. Palaniappan K., H. Ling, and G. Chen. 2012b. "Wide-Area Motion Imagery (WAMI) Exploitation Tools for Enhanced Situation Awareness". *IEEE Applied Imagery and Pattern Recognition Workshop*, Washington, DC, Oct 2012.

Blasch, E. 2013a. "Dynamic Data Driven Applications System Concept for Information Fusion". *Procedia Computer Science* 18:1999-2007.

Blasch, E. 2013b. "Enhanced Air Operations using JView for an Air-ground Fused Situation Awareness UDOP". *IEEE/AIAA Digital Avionics Systems Conference* (DASC), Piscataway, New Jersey: IEEE.

Blasch, E., G. Seetharaman, and F. Darema. 2013c. "Dynamic Data Driven Applications Systems modeling for Automatic Target Recognition". In *Proc, of the SPIE*, Vol. 8744, Baltimore, MD.

Blasch, E., Y. Al-Nashif, and S. Hariri. 2014. "Static versus Dynamic Data Information Fusion Analysis using DDDAS for Cyber Trust". *Procedia Computer Science* 29:1299-1313

Blasch, E., P. Paces, P. Kostek, and K. Kramer. 2015. "Summary of Avionics Technologies". *IEEE Aerospace and Electronics Systems Magazine* 30(9):6-11.

Blasch, E. and S. Phoha. 2017. "Dynamic Data-Driven Applications Systems (DDDAS) Concepts in Signal Processing". *Journal Signal Processing Systems*. 88: 203.

Blasch, E., M. L. Pugh, C. Sheaff., J. Raquepas, and M. Pugh. 2017. "Big Data for Space Situation Awareness". *In Proc. of the SPIE,* Vol. 10196, Edited by K. Pham, Bellingham, WA.

Blasch, E., S. Ravela, and A. Aved (Eds.) 2018. *Handbook of Dynamic Data Driven Applications Systems*. Springer, Switzerland.

Burrell, A. G., A. Goel, A. J. Ridley, and D. S. Bernstein. 2015. "Correction of the Photoelectron Heating Efficiency Within the Global Ionosphere-Thermosphere Model Using Retrospective Cost Model Refinement". *Journal of Atmospheric and Solar-Terrestrial Physics* 104:30-38.

Carnahan, J. C., and P. F. Reynolds, 2006. "Requirements for DDDAS Flexible Point Support". In *Proc. of the 2006 IEEE Winter Simulation Conference*, edited by L. F. Perrone et al., 2101-2108. Monterey, CA, Piscataway, New Jersey: IEEE.

Celik, N., A. E. Thanos, and J. P. Saenz. 2013. "DDDAMS-based Dispatch Control in Power Networks". *Procedia Computer Science* 18:1899-1908.

Chakravarthy, S., A. Aved, S. Shirvani, M. Annappa, and E. Blasch. 2015. "Adapting Stream Processing Framework for Video Analysis". *Procedia Computer Science* 51:2648-2657.

Chaturvedi, A. R. 2006. "A Society of Simulation Approach to Dynamic Integration of Simulations," In *Proc. of the 2006 IEEE Winter Simulation Conference*, edited by L. F. Perrone et al., 2101-2108. Piscataway, New Jersey: IEEE.

Chen, T., R. Bahsoon, and G. Theodoropoulos. 2013. "Dynamic QOS Optimization Architecture for Cloud-based DDDAS". *Procedia Computer Science*18:1881-1890.

Chin, T., K. Xiong, and E. Blasch. 2015. "Nonlinear Target Tracking for Threat Detection using RSSI and Optical Fusion". In *Proc. of the 2015 International Conference on Information Fusion*, edited by E. Blasch, et al., Washington, DC, 1946-1953.

Darema, F. 2005a. "Grid Computing and Beyond: The Context of Dynamic Data Driven Applications Systems". *Proc. of the IEEE* 93(3):692-697.

Darema, F. 2005b. "The Next Generation Software Program". *International Journal of Parallel Programming* 33(2–3):73–79.

Darema, F. 2010. "Cyber-infrastructures of Cyber-applications-systems". *Procedia Computer Science* 1(1):1287-1296.

Darema, F. 2011. " 2010 Multi-Agency Workshop on Info/Symbiotics/DDDAS," August.

Dunik, J., O. Straka, M. Simandl, and E. Blasch. 2015. "Random-point-based Filters: Analysis and Comparison in Target Tracking". *IEEE Transactions on Aerospace and Electronic* Systems 51(2):1403-1421.

Farhat, C., J. G. Michopoulos, F. K. Chang, L. J. Guibas, and A. J. Lew. 2006. "Towards a Dynamic Data Driven System for Structural and Material Health Monitoring," In *Proc. of the 2006 International Conference on Computational Science,* edited by V. N. Alexandrov, et al., pp. 456–464, Springer-Verlag Berlin Heidelberg.

Frew, E., B. Argrow, A. Houston, C. Weiss, J. Elston, 2013. "An Energy-aware Airborne Dynamic Data-Driven Application System for Persistent Sampling and Surveillance". *Procedia Computer Science*, 18:2008-2017.

Fujimoto, R. M., N. Celik, H. Damgacioglu, M. Hunter, D. Jin, Y-J Son, and J. Xu. 2016. "Dynamic Data Driven Application Systems for Smart Cities and Urban Infrastructures". In *Proc. of the 2016 Winter Simulation Conference, edited by* edited by T. M. K. Roeder et al., 1143-1157. Piscataway, New Jersey: IEEE.

Henderson, T. C. and N. Boonsirisumpun. 2013. "The Impact of Parameter Estimation on Model Accuracy Assessment". *Procedia Computer Science*18:1969-1978.

Imai, S., E. Blasch, A. Galli, F. Lee, and C. A. Varela. 2017. "Airplane Flight Safety Using Error-Tolerant Data Stream Processing". *IEEE Aerospace and Elecronics Systems Magazine*, 32(4):4-17.

Jia, B., K. D. Pham, E. Blasch, D. Shen, Z. Wang, G Chen.2016. "Cooperative Space Object Tracking using Space-based Optical Sensors via Consensus-based Filters". *IEEE Transactions on Aerospace and Electronics Systems,* 52(3):1908-1936.

Kahler, B. and E. Blasch. 2008. "Sensor Management Fusion Using Operating Conditions," In *IEEE National Aerospace and Electronics Conference,* eds. R. Ewing, Dayton, OH.

Kim, I. S., J. Chandrasekar, A. Ridley, and D. S. Bernstein. 2006. "Data Assimilation Using the Global Ionosphere-Thermosphere Model". In *Proc. of the 2006 International Conference on Computational Science*, edited by V. N. Alexandrov et al., Springer, Heidelberg, DE, 489-496.

Li, C-S., F. Darema, and V. Chang, 2017. "Distributed Behavior Model Orchestration in Cognitive Internet of Things Solution". *Enterprise Information Systems* 12(4):414-434.

Li, H., K. Sudusinghe, Y. Liu, J. Yoon, M. Van Der Schaar, E. Blasch., and S.S. Bhattacharyya. 2017. "Dynamic, Data-Driven Processing of Multispectral Video Streams". *IEEE Aerospace and Electronics Systems Magazine* 32(7):50-57.

Liu, B., E. Blasch, Y. Chen, A.J. Aved, D. Shen, and G. Chen. 2014. "Information Fusion in a Cloud Computing Era: A Systems-Level Perspective". *IEEE Aerospace and Elect Systems Magazine* 29(10):16-24.

Majumdar, A., A. Birnbaum, D. Choi, A. Trivedi, S. K. Warfield, K. Bladridge, and P. Krysl. 2005. "A Dynamic Data Driven Grid System for Intra-operative Image Guided Neurosurgery". In *Proc. of the 2005 International Conference on Computational Science*, edited by V. S. Sunderam, Springer, Heidelberg, DE, 672-679.

Mandel, J., J. D. Beezley, L. S. Bennethum, S. Chakraborty, J. L. Coen, C. C. Douglas, J. Hatcher, M. Kim, and A. Vodacek. 2007. "A Dynamic Data Driven Wildland Fire Model". In *Proc. of the 2007 International Conference on Computational Science*, edited by Y. Shi et al., Springer, Heidelberg, DE, 1042-1049.

Maroulas, V., K. Kang, I. D. Schizas, and M. W. Berry. 2015. "A Learning Drift Homotopy Particle Filter". In *Proc. of the 2015 International Conference on Information Fusion*, edited by E. Blasch, et al., Washington, DC, 1930-1937.

McCune, R., R. Purta, M. Dobski, A. Jaworski, G. Madey, Y. Wei, A. Madey, and M . B Blake. 2013. "Investigations of DDDAS for Command and Control of UAV Swarms with Agent-based Modeling". In *Proc. of the 2013Winter Simulation Conference,* edited by R. Pasupathy et al., 1467-1478. Piscataway, New Jersey: IEEE.

Metaxas, D., S. Venkataraman, and C. Vogler. 2004. "Image-based Stress Recognition using a Model-based Dynamic Face Tracking System". In *Proc. of the 2004 International Conference on Computational Science*. edited by M. Bubak, et al., Springer, Berlin, Heidelberg, 813-821.

Michopoulos, J. G., and S. G. Lambrakos. 2006. "Underlying Issues Associated with Validation and Verification of Dynamic Data Driven Simulation," In *Proc. of the 2006 Winter Simulation Conference,* edited by L. F. Perrone, et al., Piscataway, New Jersey: IEEE.

Michopoulos, J., P. Tsompanopoulou, E. Houstis, and A. Joshi. 2004. "Agent-based Simulation of Data-driven Fire Propagation Dynamics". In *Proc. of the 2004 International Conference on Computational Science*, edited by M. Bubak, et al., Springer, Berlin, Heidelberg, 732-739.

Morozov, A. V., A. J. Ridley, D. S. Bernstein, N. Collins, J. Hoar, and J. L. Anderson. 2013. "Data Assimilation and Driver Estimation for the Global Ionosphere–Thermosphere Model using the Ensemble Adjustment Kalman Filter". *Journal of Atmospheric and Solar-Terrestrial Physics* 104:126–136.

Neal, S., R. Fujimoto, and M. Hunter. 2016. "Energy Consumption of Data Driven Traffic Simulations". In *Proc. of the 2016IEEE Winter Simulation Conference*, edited by T. M. K. Roeder et al., 1119-1130.Piscataway, New Jersey: IEEE.

Nguyen, N. and M. H. H. Khan. 2013. "Context Aware Data Acquisition Framework for Dynamic Data Driven Applications Systems (DDDAS)". In *Proc. of the 2013 IEEE Military Communications Conference*, Piscataway, New Jersey: IEEE. 334-341.

Onolaja, O., R. Bahsoon, and G. Theodoropoulos. 2010. "Conceptual Framework for Dynamic Trust Monitoring and Prediction". *Procedia Computer Science* 1(1):1241-1250.

Patra, A. K., M. I. Bursik, J.Dehn, M. Jones, M. Pavolonis, E. B. Pitman, S. Pouget, T. Sing, P. Singla, E. R. Stefanescu, and P. Webley. 2013. "Challenges in Developing DDDAS based Methodology for Volcanic Ash Hazard Analysis - Effect of Numerical Weather Prediction Variability and Parameter Estimation". *Procedia Computer Science* 18:1871-1880.

Peng, L. and K. Mohseni. 2014. "Sensor Driven Feedback for Puff Estimation using Unmanned Aerial Vehicles". In *Proc. of the IEEE International Conference on Unmanned Aircraft Systems (ICUAS),*562 – 569.

Pournajaf, L., L. Xiong, and V. Sunderam. 2014. "Dynamic Data Driven Crowd Sensing Task Assignment." *Procedia Computer Science* 29:1314-1323.

Prudencio, E. E., P. T. Bauman, D. Faghihi, K. Ravi-Chandar, and J. T. Oden. 2015. "A Computational Framework for Dynamic Data Driven Material Damage Control, Based on Bayesian Inference and Model Selection". *International Journal for Numerical Methods in Engineering* 102(3-4):379–403.

Rao, V. H.V. S. and A. Sandu. 2014. "A Posteriori Error Estimates for DDDAS Inference Problems," *Procedia Computer Science* 29:1256-1265.

Ravela, S. 2006. "Amplitude-position Formulation of Data Assimilation". In *Proc. of the 2006 International Conference on Computational Science*, edited by V. N. Alexandrov, Springer, Heidelberg, DE, 497-505.

Ravela, S. 2007. "Two Extensions of Data Assimilation by Field Alignment". In *Proc. of the 2007 International Conference on Computational Science*, edited by Y. Shi et al., Springer, Heidelberg, DE, 1147-1154.

Ravela. S. 2012. "Quantifying Uncertainty for Coherent Structures". *Procedia Computer Science* 9:1187-1196.

Ravela, S. and A. Sandu. 2014. *Dynamic Data-Driven Environmental Systems Science*. Springer, Heidelberg, Germany.

Rodriguez-Aseretto, R., M. Di Leo, A. Cortés, and J. S. Miguel-Ayanz. 2013. "A Data-driven Model for Big Forest Fires Behavior Prediction in Europe". *Procedia Computer Science* 18:186-1870.

Roy, N., H.-L. Choi, D. Gombos, J. Hansen, J. How, and S. Park. 2007. "Adaptive Observation Strategies for Forecast Error Minimization". In *Proc. of the 2007 International Conference on Computational Science*, edited by Y. Shi et al., Springer, Heidelberg, DE, 1138-1146.

Sandu, A., W. Liao, G. R. Carmichael, D. Henze, J. H. Seinfeld, T. Chai, and D. Daescu. 2004. "Computational Aspects of Data Assimilation for Aerosol Dynamics". In *Proc. of the 2004 International Conference on Computational Science*, edited by M. Bubak et al., Springer, Heidelberg, DE, 709-716.

Shekar, S. 2016. "Dynamic Data Driven Cloud Systems for Cloud-Hosted CPS". In *Proc. of the 2016 IEEE International Conference on Cloud Engineering Workshop (IC2EW),*195-197.

Silva, W., E. W. Frew, and W. Shaw-Cortez. 2015. "Implementing Path Planning and Guidance Layers for Dynamic Soaring and Persistence Missions". In *Proc. of the 2015 International Conference on Unmanned Aircraft Systems*, 92-101.

Snidaro, L., J. Garcia Herrero, J. Llinas, and E. Blasch (Eds.). 2016. *Context-Enhanced Information Fusion*: *Boosting Real-World Performance with Domain Knowledge*, Springer, Heidelberg, Germany.

Sudusinghe, K., I. Cho, M. Van der Schaar, and S. S. Bhattacharyya. 2014. "Model-based Design Environment for Data-driven Embedded Signal Processing Systems". *Procedia Computer Science* 29:1193-1202.

Tagade, P., H. Seybold, and S. Ravela. 2014. "Mixture Ensembles for Data Assimilation in Dynamic Data-driven Environmental Systems". *Procedia Computer Science* 29:1266-1276.

Trafalis, T. B., I. Adrianto, and M. B. Richman.2007. "Active Learning with Support Vector Machines for Tornado Prediction". In *Proc. of the 2007 International Conference on Computational Science*, edited by Y Shi et al., Springer, Heidelberg, DE, 1130-1137.

Uzkent, B., M. J. Hoffman, and A. Vodacek. 2016. "Integrating Hyperspectral Likelihoods in a Multidimensional Assignment Algorithm for Aerial Vehicle Tracking". *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 9(9):4325-4333.

Virani, N., J-W. Lee, S. Phoha, and A. Ray. 2015. "Learning Context-aware Measurement Models". In *Proc. of the 2015 IEEE American Control Conference (ACC)*, Chicago, IL, 4491-4496.

Wang, L., D. Chen, W. Ma, Y. Wu., and Z. Ding. 2014. "DDDAS-Based Parallel Simulation of Threat Management for Urban Water Distribution Systems". *Computing in Science and Engineering,* 16(1):8-17.

Wu, R., B. Liu, Y. Chen, E. Blasch, H. Ling, and G. Chen. 2016. "A Container-based Elastic Cloud Architecture for Pseudo Real-time Exploitation of Wide Area Motion Imagery (WAMI) Stream". *Journal of Signal Processing Systems*88(2):219-231.

Yang, C. and M. Bakich. 2005. "Pose Angular-Aiding for Maneuvering Target Tracking," In *Proc. of the 2005 International Conference on Information Fusion*, edited by E. Blasch, 1-8.

Zheng, Y., E. Blasch, and Z. Liu. 2018. *Multispectral Image Fusion and Colorization.* Bellingham, WA: SPIE Press.

AUTHOR BIOGRAPHIES

ERIK BLASCH is a Program Officer at the Air Force Office of Scientifc Research (AFOSR). He received his BS from MIT, six MS degrees, and PhD from Wright State University. He has compiled 750+ papers, 4 books, 21 patents, and 25 tutorials. He is a recipient of the Military Sensing Society Mignogna data fusion award, past president of the International Society of Information Fusion, AIAA Associate Fellow, SPIE Fellow, and IEEE Fellow. His email address is erik.blasch.1@us.af.mil.