Chapter 32
DDDAS: The Way Forward

Erik Blasch, Sai Ravela, and Alex Aved

Abstract This book sought to capture the highlights of DDDAS over the last two decades, with an emphasis on the key areas of development including: theory, modeling, and examples. DDDAS seeks to leverage high-dimensional models to provide data that augments real time estimation, analysis, and control. Many examples were presented that highlight recent approaches, developments, and use of the DDDAS concept towards advancing science through data understanding, analysis, and discovery. The future would further develop these DDDAS concepts towards a better understanding of scientific principles, engineering systems design, and multi-domains applications. DDDAS will leverage and influence such areas as machine learning analytics, multi-domain autonomy, and contextual awareness.

32.1 DDDAS Methods for Systems Science

The book has demonstrated that many applications have been furthered from the use of the DDDAS paradigm. DDDAS advances presented in the book highlight three areas of analytics, autonomy, and awareness. DDDAS methods incorporate dynamic data that predated the trends in big data *analytics*. The future techniques will align with the efforts in artificial intelligence and machine learning that leverage data from high-dimensional modeling.

A second area includes the many applications in *autonomy* to include sensing, robotics, and filtering across many domains: space, air, and ground. The DDDAS methods focused on the machine processing of techniques; however developments

E. Blasch (✉)
Air Force Office of Scientific Research, Air Force Research Laboratory, Arlington, VA, USA

S. Ravela
Earth, Atmospheric and Planetary Sciences Massachusetts Institute of Technology, Cambridge, MA, USA

A. Aved
Information Directorate, Air Force Research Laboratory, Rome, NY, USA

E. Blasch et al. (eds.), *Handbook of Dynamic Data Driven Applications Systems*,
https://doi.org/10.1007/978-3-319-95504-9_32

Table 32.1 DDDAS methods applied to awareness

Awareness	Models/Measurements	Contributions
Structural health	Solids models Temperature measurements	Self-healing damage recovery Fly-by-feel aircraft
Environment	Weather models Wind measurements	Autonomous UAVs Air-breathing engine safety
Space situation	Atmospheric models Electron density	Resident object tracking Satellite detection
Situation	Terrain models Target kinematics	Knowledge-aided radar Multi-sensor planning
Computational	Data flow models Buffer measurements	Computer vision surveillance Container-based optimization
Cyber	Cyber-physical models IoT, SCADA measurements*	Power/micro grid management System level security

*Internet of Things (IoT), Supervisory Control and Data Acquisition (SCADA)

will be aligned with user decision support, scenario assessment, and real-world deployment of the methods towards practical applications.

In general, the DDDAS themes include improvements in *awareness*, such as space situation awareness (SSA), structural health awareness, and environment awareness; where newer themes have emerged in situation awareness, computational awareness, and cyber awareness (as shown in Table 32.1). In many cases, awareness could be replaced by monitoring the surroundings of the application. DDDAS builds on situational monitoring to leverage high-dimensional models for real-time, dynamic, and run-time assessment.

Other demonstrated examples included bio-medical approaches to medical diagnostics, human health, and urban pandemics. The rich exploration of DDDAS for the sciences is only emerging. With data analytics, machine leaning, and artificial intelligence, these areas would continue to grow. DDDAS fosters the use of high-dimensional, large-scale, and big data models to augment performance. The book follows the advancements since the 2010 workshop which had a focus on the sciences [1]. The developments moved from situation awareness to that of situation understanding.

32.2 DDDAS Has Universal Appeal

32.2.1 Paradigm for Theory-Data Symbiosis

Throughout time man has sought to learn from data using to better understand the world around them. From a physics-based analysis, DDDAS formalized this process, initially for computational science, but subsequently for different applications beginning in the first decade before the introduction of big data and recently with data sciences. The DDDAS paradigm seeks to introduce the use of high-dimensional

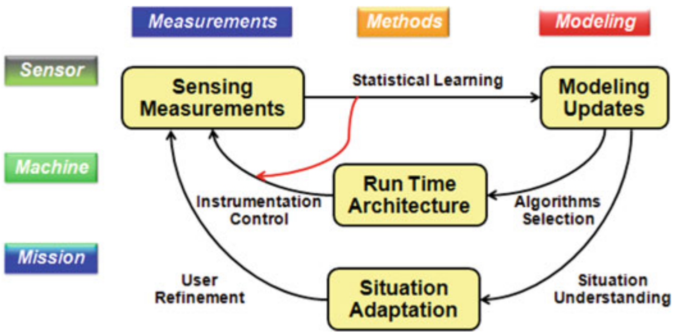

Fig. 32.1 The DDDAS loop

models (theory) as a method for accessing simulated data, when the environmental analysis cannot be fully measured. Pragmatic collection of *data*, whether sparse or voluminous, can be carefully processed to better understand the world and support model refinement. DDDAS seeks to leverage the foundations of mathematics [2] for modeling and control. The ***theory-data symbiosis*** is the hallmark of the DDDAS approaches. Figure 32.1 highlights the DDDAS loop when considering awareness (sensor, machine, or mission) to that of the measurement collection, modeling, and methods used for the theory-data symbiosis.

Learning models from data and producing models from theory [3] are both limiting; however the symbiosis occurs at all levels of abstraction. Symbiosis takes many forms: at the highest level, learned models are coupled with derived models, while at the lowest level theory constrains learning from data, from which data provides the mechanism for estimation and control. Key aspects of many of the solutions included ***multi-dimensional, multi-resolution, multi-sensor, and multi-perspective*** analysis. The diversity of information supports the opportunity to refine models with non-traditional sensing. Examples were provided of emerging concepts that include the use of Internet of Things (IoT) data in addition to electrical output for cyber-physical power and micro-grid analysis, urban monitoring from text and space data, as well as imagery and strain measurements for structural health monitoring. In each case, there was a benefit for management, sensor collection, and healing; respectively. The *future applications* of DDDAS will incorporate public domain information emerging in complexity from the environment (e.g., weather), sensors (e.g., polarization), and objects (e.g., power grids).

32.2.2 Mitigates the Curse of Dimensionality

DDDAS mitigates the challenge of big data collection and analysis from information fusion [4]. From a theoretical point of view, the curse of dimensionality is mitigated through the ***intelligent collection of data***. Many theoretical models from physical

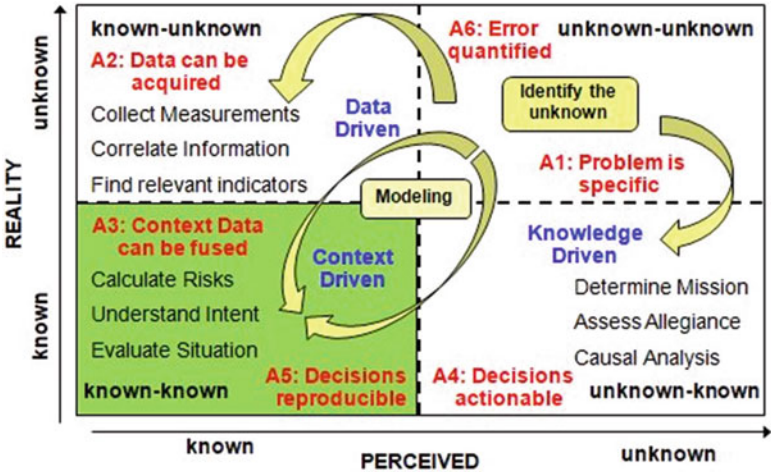

Fig. 32.2 DDDAS for context driven solutions to the unknown unknowns, where (A1, … A6) represent assumptions for analysis

to social, behavioral, economic, and cultural phenomenon are reduced to a set of salient parameters. In a similar way, the limitations of mathematical tractability can be supported with the assumption that there is a fundamental set of information that is needed to support run-time applications. In the book, many examples highlighted approaches to support the data analytics with that of data collection and models, as shown in Fig. 32.2. Essentially, DDDAS will *push the frontier* of explaining the unknown unknowns; such as how the unknown weather (e.g., hurricanes) effects on the unknowns on sensors (e.g., autonomous aircraft) for control and action.

DDDAS is ***valid across many scales*** from recent trends in internet of Things (IoT) data and cyber physical systems (CPS) to that of high-dimensional environmental models [5]. The many examples presented in the book demonstrate that DDDAS works across many spectrums such time, space, frequency, and modalities. DDDAS provides solutions for multi-resolution situations from the local to the global spatial, micro to macro frequencies, and small to large time scales. Examples were shown from time series, language processing, and structural analysis. The *explosion of data* will be an area were DDDAS learns new models, uses the models for surrogate information, and provides predictive multi-dimensional control for enhanced performance.

32.2.3 A Prediction and Discovery Instrument

The power of DDDAS is to use the simulated models so as to predict the future behavior of systems. As with the curse of dimensionality there is the analysis of the unknown unknowns. To be able to utilize a model to predict the ***unknown***

unknowns through simulation is a unique feature of DDDAS [6]. To employ the DDDAS methods, assumptions are made (Fig. 32.2) such as (A1) problem is specific, (A2) data can be acquired, (A3) context data (from the models) can be fused, (A4) decision are actionable such as in future collections, (A5) decisions reproducible (for model updates), and (A6) error can be quantified. The book begins with methods for uncertainty quantification (A6) and ends with domain-specific examples (A1). The domain-specific application supports knowledge-driven approaches, while the error-analysis supports the data-driven approaches. With modeling from various methods of the environment, structures, energy, and network analysis; high-dimensional information is used to support DDDAS approaches for context-based systems support.

32.3 Emerging Opportunities

As highlighted in Chap. 1, DDDAS include: (1) real-world applications, (2) instrumentation methods, (3) modeling and simulation, and (4) systems software. The future of each area and their intersection should forage new efforts using the DDDAS methods.

32.3.1 Applications Systems

DDDAS can be applied to specific problem domains which resolve around the fidelity of the models of those communities. Emerging communities in big data (e.g., CPS, IoT), data control (e.g., fog computing), and data science (e.g., multimedia analytics) augment the traditional methods for engineering analysis, as shown in Fig. 32.3. Such information as terrain information can be used for urban tracking while the intersection of structures, environments, and avionics is shown in Fig. 32.3 as a future application in the fly-by-feel autonomous UAV. Big data metrics includes velocity, volume, veracity, and variety (4 V's) while DDDAS has focused on the ***value of data*** – whether in collection or from models. DDDAS focuses on value by integrating the correct simulation data into the model and assessment for updates to control the big data collection issues.

It would difficult to restrict DDDAS to specific application areas; however the book highlights many that could inspire other paradigms such a drug delivery in medicine, aid distribution for emergency disasters, and social policies for effective management of energy and food resources.

32.3.2 Instrumentation

Specific sensors are being designed at every scale, while at the same time there is a growing amount of data being collected from all types of sensors, from the

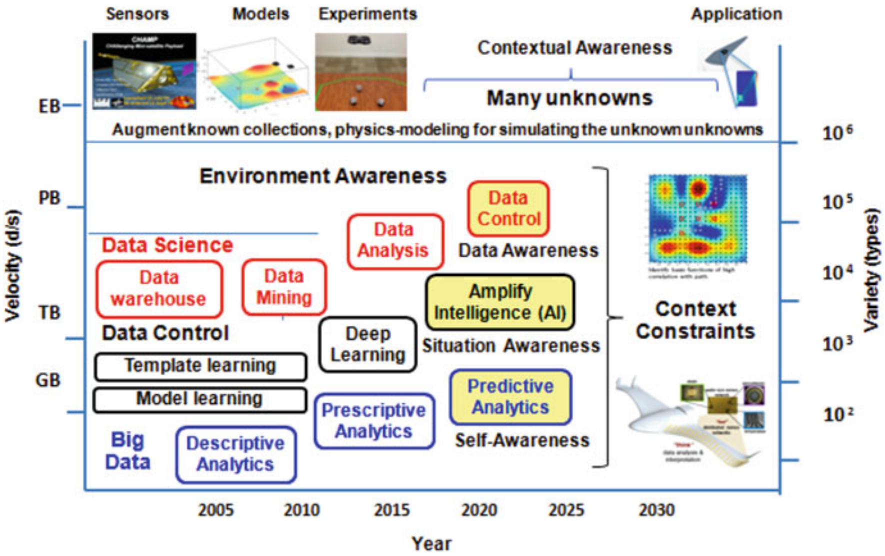

Fig. 32.3 DDDAS developments for data science, data control, and data size

physical to the human. Future instrumentation systems support the processing, exploitation, and dissemination of information for knowledge (shown in Fig. 32.4). The ability of physics-based and human-derived information fusion (PHIF) extends the joint sensing capability over distributed situations. A second construct of instrumentation is that the sensor design and collection includes the processing and exploitation of the data from the sensors. Using a sensor model can help better understand the data that is being collected and assessed. A third concept is the dissemination of the information for indexing and analysis. The instrumentation methods need to consider where the data is being sent for various scale analysis. For example, local data collections could support a single UAV for safe flight, while that information can be sent to air traffic management for a global analysis of the swarm of UAVs operating in various weather conditions. The future of DDDAS will include advanced computation methods for indexing of data, ontological models to categorize the data for human and machine analysis, as well as the control and management of instrumentation data for distributed networks.

32.3.3 Modeling and Simulation Methodology

The growth in data science helps to enhance model building, simulation analysis, and prediction for domain applications. Many times, the models are developed for specific communities in specific forms. Hence, one future area is model matching such that multiple types of information can be used (e.g., environment and structures

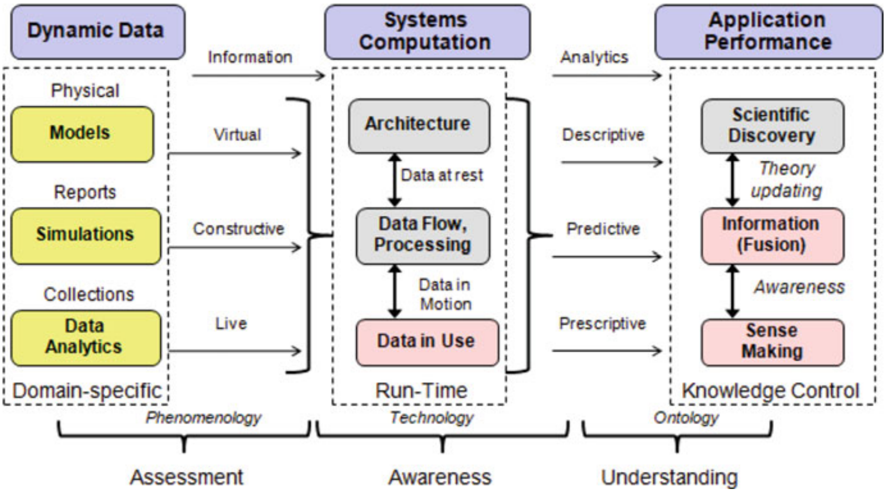

Fig. 32.4 DDDAS Future concepts for situation assessment, awareness, and understanding

models). Chapter 1 highlighted the data-assimilation loop, but bringing in multiple (modal) data assimilation loops is still a challenge. For simulation, there is a need for effective and efficient methods to support run-time operations such as dissemination the full scale results to the on-line system for performance optimization. Deep learning is a method that first learns the global elements and then focuses on learning the specific variations that change (e.g., learning the general aspects of a vehicle and then focusing on the moving parts such as door opening and closing variations or the environmental changes do to luminance effects). Learning over independent paradigms needs to be integrated for useful simulations. As with all DDDAS-inspired methods, the future goal of DDDAS is to bring together the models, simulations, and data analytics.

32.3.4 Systems Software Computation

The field of high-performance computing has many directions including data flow architectures (e.g., container-based processing), electronic design (e.g., quantum computers and computation), as well as high-end to run-time analysis (e.g., edge computing). The measurement collections of DDDAS can be made more efficient through data flow architectures. The high-dimensional modeling of DDDAS could be developed for quantum computing. Finally, the integration of modeling at a cloud computing center can be integrated with fog computing and edge computing for large scale data collections.

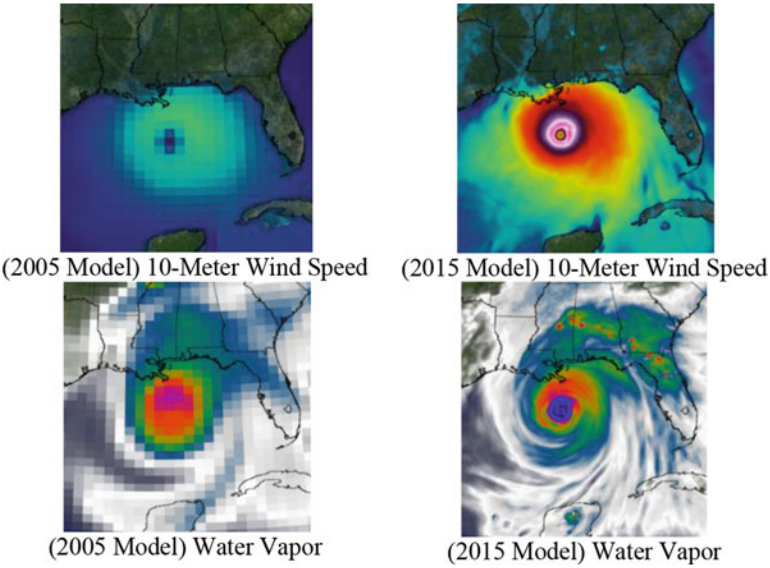

Fig. 32.5 Contribution of modeling in support of DDDAS [7]. Each image shows the near surface wind speed and water vapor of Hurricane Katrina on Aug. 29, 2005, but at different resolutions. The left image is at a 50-km resolution, the resolution of most global models in 2005. The right image shows a 2015 version of the Goddard Earth Observing System model, Version 5 (GEOS-5), at a 6.25-km global resolution. (***Credits: NASA Goddard Space Flight Center/Bill Putman, accessed at:***https://www.nasa.gov/feature/goddard/since-katrina-nasa-advances-storm-models-science)

32.4 Example: Hurricane Prediction

As highlighted in the Chap. 1, the modeling from the *data assimilation loop* can support the *sensor reconfiguration loop*. An example case was presented in hurricane analysis. Figure 32.5 showcases the importance of DDDAS-like processes of the power from the advancements in modeling. The hurricane Katrina incident was based on the capabilities to capture the current data, predict the direction of the hurricane, and determine the “control” of the population and disaster relief. As seen from high-dimensional NASA modeling [7], the updates from 2015 methods demonstrate higher resolution, lower uncertainty, and direction assessment of the hurricane as it moved towards the coastline.

32.5 Conclusions

The DDDAS community is rigorous, unique, and interdisciplinary. The information presented in the book highlights advances in DDDAS with emphasis on the integration of instrumentation, modeling, analytics, and architectures. Hopefully the book presented useful ideas to the reader to inspire their own developments and applications. The organization and methods presented provide a discussion for which the community can utilize DDDAS paradigms for scientific discovery, information analytics, and sense-making for real-time awareness.

Acknowledgements The editors, and contributing authors, would like to thank AFOSR for their support and the guidance from Dr. Frederica Darema who developed the DDDAS concept and inspired a generation of researchers. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of the United States Air Force.

Bibliography

1. F. Darema, *Multi-Agency Workshop on Info/Symbiotics/DDDAS: The power of Dynamic Data Driven Application Systems*, Report Output from AFOSR, August 2010
2. D.S. Bernstein, *Matrix Mathematics: Theory, Facts, and Formulas with Application to Linear Systems Theory* (Princeton University Press, Princeton, 2005)
3. F. Gini, M. Rangaswamy, *Knowledge Based Radar Detection, Tracking, and Classification* (Wiley-Interscience, Hoboken, 2008)
4. E.P. Blasch, E. Bosse, D.A. Lambert, *High-Level Information Fusion Management and Systems Design* (Artech House, Norwood, 2012)
5. S. Ravela, A. Sandu, *Dynamic Data-Driven Environmental Systems Science*, International Conference, DYDESS 2014, LNCS 8964 (Springer, Cham, 2015)
6. L. Snidaro, J. Garcia Herrero, J. Llinas, E. Blasch (eds.), *Context-Enhanced Information Fusion: Boosting Real-World Performance with Domain Knowledge* (Springer, Cham, 2016)
7. B. Puttman, *NASA Goddard Space Flight Center,* "Since Katrina: NASA Advances Storm Models Science," Aug. 21, 2015. Accessed 2018 at: https://www.nasa.gov/feature/goddard/since-katrina-nasa-advances-storm-models-science