Exploring Data Management Challenges in EDA

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Prologue

Technology interoperability is a critical need in the evolution of industry collaboration. To facilitate that, Si2 formed the Technology Interoperability Trajectory Advisory CouNcil (TITAN) to explore how to enable global technology interoperability for silicon-to-system solutions in critical vertical markets. TITAN has three satellite arms (SPEED API, Data Management & Workflow, Multi-Die Heterogenous Integration) to help realize its vision. The contents of this whitepaper arise from the findings of a recent survey conducted by the DMW Satellite of Si2-TITAN.[1]

Acknowledgements

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Exploring Data Management Challenges in EDA

Abstract

We live in a data-driven world and the chip (including IP, ASIC, SoCs, and Systems) design, verification, manufacturing, and test teams are seeing an explosive growth in data. According to a recent survey conducted by Si2-TITAN, a typical engineer spends 3 hours every week on average in various aspects of data processing, leading to an estimated $750M in annual costs to the electronics industry. It is clear that data management is a huge challenge, and it is imperative that we identify solutions for navigating these hurdles in an efficient manner. In this whitepaper, we share the results from that survey and our recommendations for addressing some of the pressing data management challenges.

1 Motivation for focus on Data Management

Everyone has probably heard the saying that "data is the new oil", as it is omnipresent. Study after study shows evidence to this enormous growth in data being generated in almost every facet of our lives today. Not surprisingly, the electronics industry landscape - which spans the design, verification, analysis, test, and manufacturing domains - is no exception to this explosive growth in data. Consequently, the engineering teams are forced to spend significant time in collecting, curating, processing, transforming, analyzing, storing, securing, and sharing the data. This is further compounded by the fact that most design houses use tools and methodologies provided by multiple suppliers and are thus faced with data interoperability issues. [2,3,4]

Data management connects people and processes to optimize the use of data so better decisions and business results are achieved. Towards that end, the DMW satellite team conducted a survey in Fall 2022 to identify data management challenges and opportunities that span design, verification, analysis and test domains, from ASICs and processors to SOCs. In the following, we share the results from that survey, challenges to the data management ecosystem, and propose our recommendations going forward.

2 Survey details and analysis of results

2.1 Survey Overview

The survey was sent to several practitioners in the industry. About 60% of the survey respondents were EDA Software Developers, and 20% of them were Project Managers. The rest of the participants were Test Engineers, RF/analog Design Engineers, and Board/System Engineers. In the following we provide more details about our survey process, the sample of questions posed, and a compilation / pareto analysis of the responses.

Details

While putting together the survey, the satellite team looked at various data aspects, including interoperability between tools, traceability to sets of requirements, and engineer productivity. To generate a comprehensive survey, the team brainstormed key functions of data management, such as:

- Interoperability between tools
- Collaborate effectively on a complex design
- Traceability to set of compliance requirements
- Data, IP Reuse
- Handoffs which affect time to market
- Using data to make technical and/or business decisions
- Types of data to be stored – what can be stored – database storage
- Version control
- Differences in data formats across the tools
- Cloud adoption and readiness

As one can imagine, the scope of data management is too big. To keep the survey to a manageable size, a key discussion point in our satellite teams was to narrow down to a set of areas that needed the most urgent attention and also benefit a larger pool of practitioners. To help with that goal, we referenced many existing publications in this area as well as other surveys done by Si2 and others. The reader is referred to the References section to get more details about these sources.

After several weeks of interesting discussions, the DMW Satellite team compiled a list of survey questions that consisted of the following themes:

A. Basic Data Management
B. Interoperability
C. Time to results (TTR), time to market (TTM)

Here is a sample of the questions that were posed to the survey audience.

1. What are the trends and drivers for better data management?
2. What would you say are the primary functions of data management?
3. What are the challenges in your data management infrastructure?
4. Which of the following elements would have the biggest impact on your product development cycle time?
5. Where are the current workflows you see the greatest product development data management challenges? Pick up to 3
6. What category of data has the biggest data management challenges?
7. How is data shared between design and test teams?
8. Where does your company deploy in-house tools to fill gaps in EDA or test workflows?

Appendix 5.2 shows the complete list of questions posted as part of this survey.

2.2 Survey Results and Analysis

The responses from the survey provided several interesting insights. In the following, we summarize the key results.

1. Almost 80% of the participants said that Product Complexity was driving the need for better data management.

2. About 2/3 of the respondents said it takes 1-3 months and 1/3 of the participants said that it takes more than 3 months to correlate test data with simulation data. An interesting point to note is that not a single person said that it took less than a month to do this correlation.

3. The top three most time-consuming data management tasks as shown in Figure 1 were
    3.1. Locating and accessing the data needed
    3.2. Reducing, sorting, organizing data for processing
    3.3. Correlating pre-silicon design and post-silicon test data
    * An interesting revelation from the response to this question was that not many considered storing of big data as a big challenge.

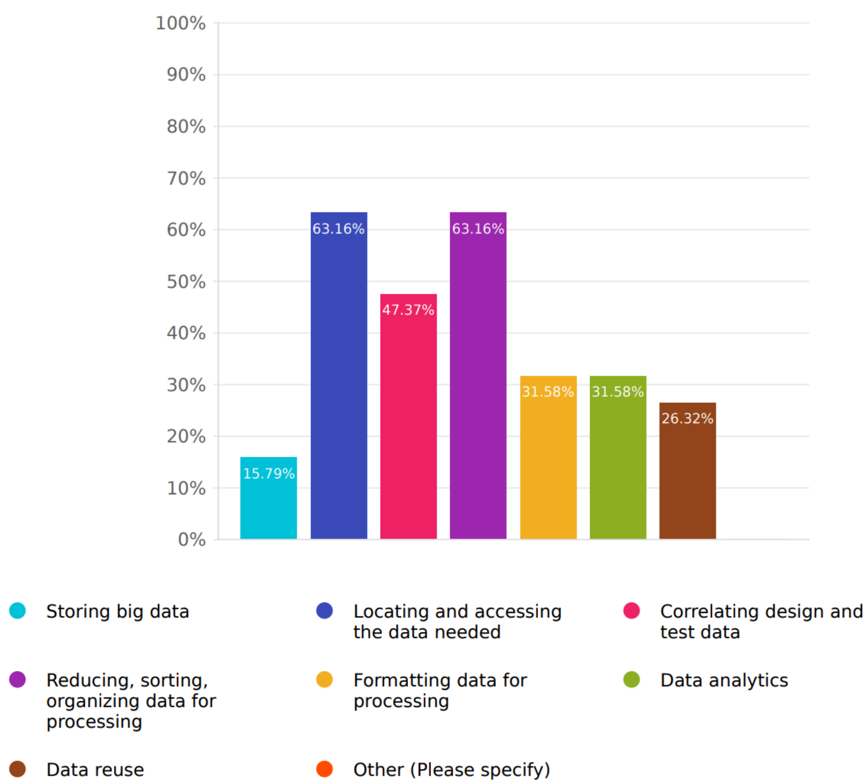

Figure 1 Time Consuming Data Management Tasks

4. From a productivity perspective, we found that significant time was spent on collecting, formatting, reducing, processing, analyzing, and correlating data. 26% of respondents said that a typical engineer in their team spends 3-5 hours per week and 42% of them said that they spent more than 5 hours per week in data processing as shown in Figure 2. This is a staggering statistic, indeed.

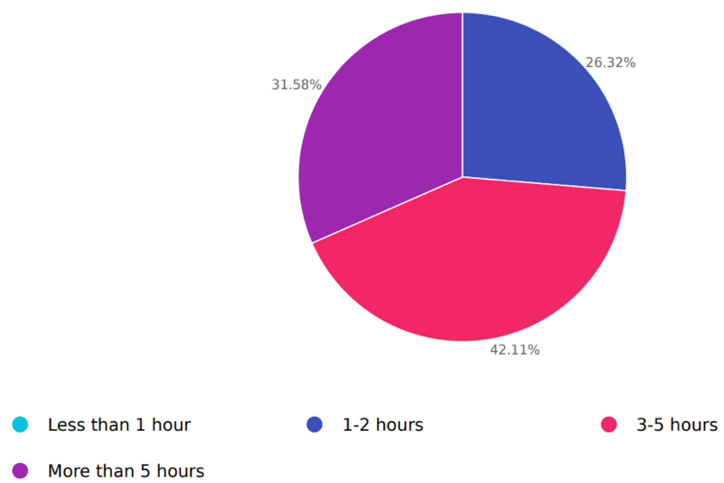

Figure 2 Time Spent Processing Data

5. For the question on IP management challenge, there was no significant winner among the following options that were given as possible responses:
    5.1. Tracing data and IP and/or meta data linkage between steps in a flow
    5.2. Facilitation of IP reuse within teams
    5.3. Facilitation of IP reuse between different teams
    5.4. Configuration management of IP / version control

6. An overwhelming majority (~80%) of participants stressed the need for EDA vendors to standardize data formats and APIs.

7. Some of the requests from survey respondents for standardization include:
    7.1. Standardize tool outputs - DRC report, timing report, utilization of std cell area for example
    7.2. Liberty format should be taken under IEEE SA and functionality expanded
    7.3. Modelling standards for system ID
    7.4. Logic Simulation Format: FSDB OASIS TEXT format
    7.5. Input and output data format standardization for EDA Power/Thermal/Signal integrity flows.

8. More than 50% of respondents said that they use 3 to 5 different formats, while an additional 15% said that they use 6-10 different formats as shown in Figure 3. What was more surprising was the fact that some 30% of the respondents said they are juggling around more than 10

different data formats!

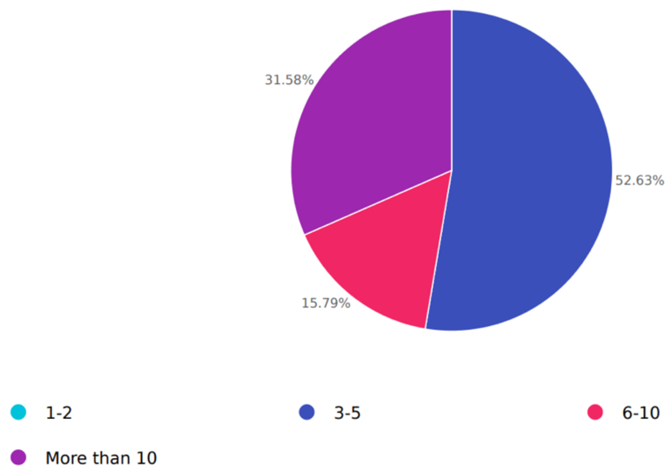

Figure 3 Number of Data Formats Used

9. More than 80% of the participants said that "Integrating data from disparate sources" was either their most severe or second most severe data management challenge. It was followed by "Collecting, processing, validating data", which was voted by 65% of the respondents as the most severe or second most severe data management challenge.

10. The respondents ranked "Communicating between multiple data management systems" as their most challenging data management issue. It was closely followed by "Managing multiple data repositories".

11. "Ability to interchange data across tools and teams" was chosen as the workflow element with the biggest impact on product development cycle times.

12. More than 60% of respondents said that their company deployed in-house tools in Tool interoperability, Analytics to fill gaps in EDA or test workflows. And 50% of them said that their company invested in custom tools and tools for Simulation/test data management.

13. The survey had a few different questions on cloud adoption, and here is the response summary: More than 90% of respondents said that they are either already using or exploring cloud storage.
    - 70% of survey participants are either currently exploring or willing to investigate cloud verification techniques.
    - Only about 30% are using SaaS solutions

2.3 Key takeaways from the Si2 survey

As detailed in the previous section the survey provided several valuable insights into data management, underlying challenges, and opportunities thereof. For instance, one key result from the survey was the fact that a typical engineer spends 3 hours every week on average in various aspects of data processing. This leads to an estimated $750M (see Appendix 5.1 for how we arrived at this cost) in annual costs to the electronics industry. Any effort towards reducing the average data management time of 3 hours per week could result in huge cost savings.

The survey also shows the use of many data formats (3+) in a typical design flow, and a desire to produce industry-wide standards that can help bring efficiency.

The key take-aways and needs from the survey could be grouped into the following:

- Managing multiple Data formats
- APIs & interoperability
- Meta-data traceability

In Section 3 we discuss in some detail the work done by DMW in addressing these challenges to the data ecosystem.

3 Data Ecosystem Challenges

3.1 Data Ecosystem

Managing big data in the product development ecosystem for complex products is challenging for customers. This is especially true for designs that are analog mixed signal in nature where there is not only digital functionality to verify but analog performance to verify. Performance of analog features is influenced by many parameters, and the data produced during verification is immense. There are multiple considerations for building a proposed solution.

1. Product development data handling must consider the digital twin (pre-silicon design) and the physical system (post-silicon test) which are both integral parts of this ecosystem. See Figure 4.

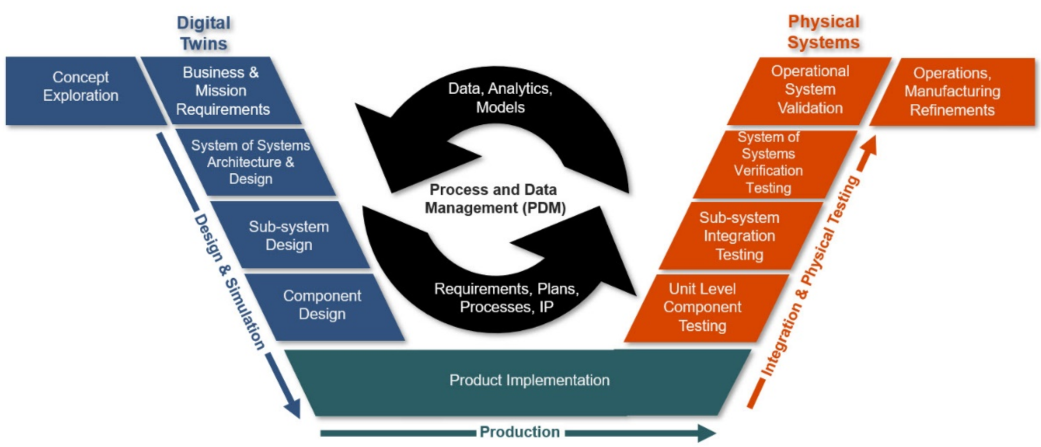

Figure 4 V-Model of Digital Twin Ecosystem

2. As can be seen by the survey data, 5-10 software tools may be utilized by a particular engineer. This diversity of tools used is similar for testing hardware as well. Considering collaboration among multiple engineers on a project it is easy to see that a data management solution needs to

consider 20 or more tools may be used in product development and a wide range of data formats need to be considered.

3. Traditional data handling of storing raw data is insufficient in today's world. Not only is manual processing of data tedious (up to 30% of an engineer's time is used processing data), but making optimum use of the data is lacking as the data has no context on how it was generated and under what conditions – in other words, no traceability.

To address these issues the solution should consider the following:

- How to manage multiple data formats
- APIs and interoperability
- Adding meta-data traceability
- Data base management

3.2 Managing multiple data formats

Data produced by tools today is in a myriad of formats, some specific to individual tools. There may be dozens of data formats utilized in a design and test product development effort, making the task of data management difficult. A "hub and spoke" solution using a common data format is one technique that can be utilized.

Consider a reasonable situation where there are ten different tools utilized in a product development workflow and N major data formats utilized. In order for the data to be interchanged between all tools in a traditional manner Nx(N-1) format to format interfaces would be required. For the case of six data formats being used in a workflow 30 interfaces would be required. This is impractical for the myriad of tool vendors to implement and support.

A graphical representation of the hub and spoke model is shown below in Figure 5. In this approach a common data format is utilized. One interface between a given data format and the common data model is required. For N number of different data formats, up to N interfaces (in this case 4) are needed. A traditional format to format data interface would require up to (4x(4-1))=12 interfaces.

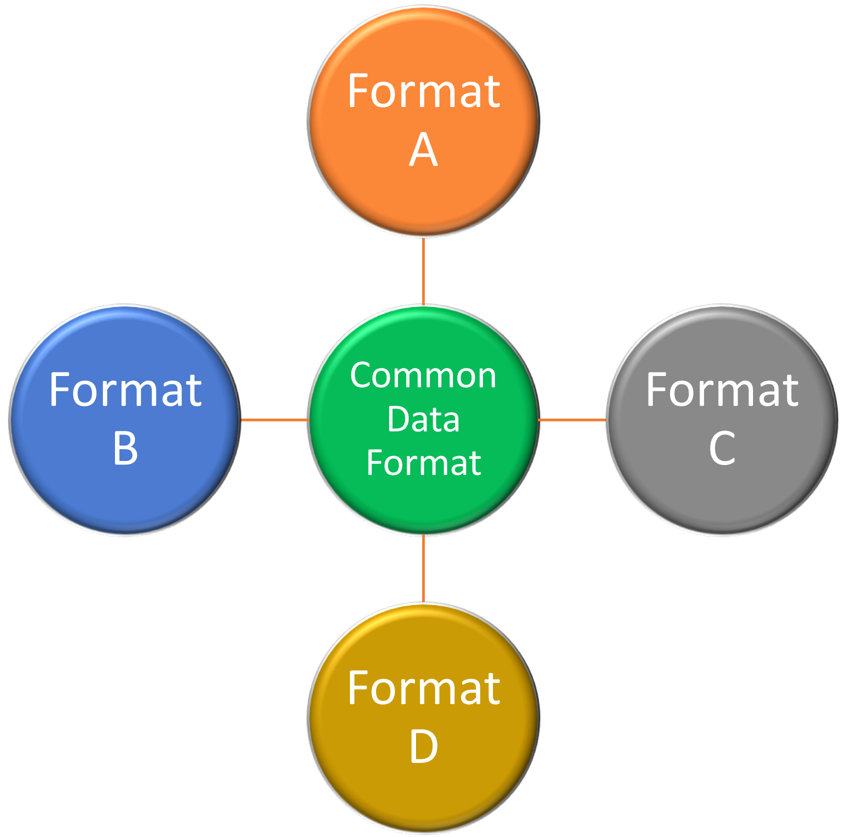

Figure 5 Hub and Spoke Model

Data management connects people and processes to optimize the use of data to achieve better business results. The common data model lowers the barrier for data connection to address this overarching principle.

There is not one magical type of hub data format that works for all use cases. The format chosen depends on the use case. That said there are two types of CDM formats that can be suggested, JSON and HDF5. Both are open, industry accepted standards, and each has pros and cons.

HDF5 is a binary format and a good choice due to its overall capability and universal industry acceptance (it is open source). It supports large complex data sets, as well the ability to extract portions of the dataset. This is useful for time series data where the user only needs to extract a small portion of the data versus loading the entire data set which could be many gigabytes in size. It functions as a self-contained data store. Some generalized HDF5 advantages:

1. Widely accepted, open source
2. Hierarchical
3. Big, complex data
4. Binary format – more compact storage than other formats
5. Heterogeneous data storage – many types of data within the same file
6. Esoteric data for special purposes
7. Support of parallel I/O
8. Support for most programming languages

9. Metadata storage
10. Random access (portion of dataset)
11. Faster than database systems
12. Supports ML

Disadvantages:

1. Complex standard
2. File corruptions are generally un-recoverable and not human readable – it's a binary file
3. Difficulty with distributed architectures
4. Not friendly for web applications, not portable
5. Lack of multi-platform support

The JSON data exchange format is widely accepted and supports web applications. It also works well with Python which is a widely-used application-level language. Python is the language of choice for connecting APIs together in an open ecosystem.

JSON advantages:

1. Widely accepted, open source, language agnostic
2. Hierarchical
3. Simple, easy to manipulate, and learn
4. Fast and efficient
5. Self-describing
6. Handles complex data
7. Ease of data sharing serialization, deserialization
8. Browser support from all programming languages
9. Designed to run with MongoDB
10. Can be read by humans and machines

Disadvantages:

1. No support for comments
2. More vulnerable to security breaches
3. No date data type

A recommendation of data format by use case is shown in Table 1 below.

Table 1 CDM file format choices

Use Case	HDF5	JSON
Fast Parsing and Reading – low latency	X	
Support popular AI/ML frameworks	X	
Supports data slicing (ie time based simulation/test data)	X	
Complex data, big data	X	X
Complementary to databases	X	X
Good for network storage, cloud applications		X

Both data formats can be used for a CDM architecture, and others can work, too.

3.3 APIs and Interoperability

To promote team collaboration, the data should be universally consumable and therefore able to work within multiple operating systems and be cloud compatible. A common API can be used to manage communication and data between various services utilized in a workflow and the various clients. Like the common data model, the common API reduces the number of API connections that need to be made. An established open architecture approach with uniform interface is needed to propagate a solution and there are multiple architectural choices.

An example of an API that can work in this capacity is the representable state transfer architecture as shown below in Figure 6. It acts as a mediator between the client and service and helps maintain security, control, and authentication. Information is typically delivered in a JSON file which is language agnostic.

Key characteristics are:

- Client/server architecture
- Secure: No client information is stored between requests, each request in unconnected
- Stateless – all information to understand a request is included in the request
- Cacheable and non-cacheable data
- Uniform interface
- Data transferred in a standard way
- Layered hierarchical server organization – servers with different tasks

Figure 6 API Example

3.4 Metadata Traceability

Metadata is essential to provide traceability which is important not only in the highly regulated automotive and aerospace industries but broadly important to provide context as to how the data was generated and under what conditions. In applications where data will be accessed by data bases or analytic post processing is used, metadata is required to enable these capabilities. Metadata can include workspace name, simulation/test tool type and version, date, parameters such as states, temperatures, voltages, material properties, etc.

As mentioned, metadata can be stored with a variety of file types including JSON and HDF5 files. Metadata can be provided with the client file when it is produced or added to the file after its produced. For data management automation a "results listener" function can be used for adding metadata to the data when it is produced real time. The function of the results listener is to work with the various tools producing data, understand when a result is available, tag the data with any other applicable metadata, then send the file to storage as shown in Figure 7.

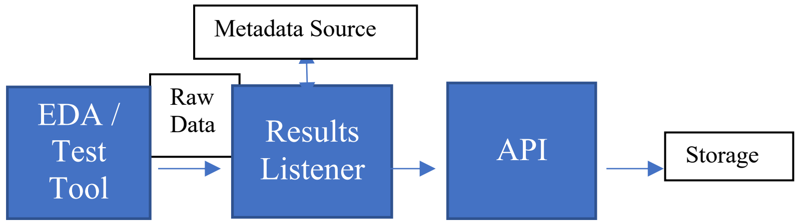

Figure 7 Metadata Tagging Process

Data tagging helps enable analytics. When metadata is utilized, raw data can be reduced and filtered in an automated way so the end user can get to the data they are interested in. Metadata makes databases much more powerful and it provides more information to key off of. Tagged data can be used to view data in specific ways which can bring insights to the user and provide statistical results over a specific range of conditions. Metadata enables AI driven tools to draw correlations across big datasets or multiple data sets which may not be visible using manual methods.

3.5 Storage and Databases

For managing data, a storage hub or repository is needed. The storage hub manages all data so it can be made easily and quickly accessible, traceable, and re-usable. Data storage management works in conjunction with the REST API to provide access, authentication, and security.

Data in storage can include many types of data, and the data produced by simulation and test (the focus here) is managed alongside the other data types. The data storage can be on-premise, off-premise or a hybrid of the two. The API connects directly to the storage management system of which there are many options which are driven by the end company need.

The utilization of databases is key when there are many data records and there is a need to quickly access and re-use vast amounts of data generated. If the data is likely structured (the format contains organized information classifying the content – like specific rows and columns) an SQL database can be used to locate a particular record quickly thru queries. An SQL database is also known as a relational database. In most cases the structured data is utilized for a specific purpose which limits flexibility. For example, changes in data requirements and data fields have the consequence of needing an update of all structured data which can be a large expense. Additionally, SQL databases are not efficient, as the data being stored can only be scaled in one dimension – vertically. MySQL and PostgreSQL are examples of open, industry database tools.

Over 80% of enterprise data is unstructured – there is no pre-defined organization of the data. This is especially true in the engineering field. Databases that handle unstructured data have an advantage that additional fields and requirements to the data can be added and it does not require an update to the data that is stored. The data is undefined which increases adaptability. The other advantage is that the data can be loaded quickly and easily, without any additional steps associated with structured data. The main disadvantage of a database handling unstructured data is limited capability to query data, which may also limit analytics. Because of the non-formatted nature of the data, more expertise is required to prepare and analyze the data. Databases handling unstructured data are also known as non-relational databases. MongoDB is an example of a widely used database tool that works across a variety of applications and services.

A hybrid approach can be utilized when an enterprise needs the flexibility of an unstructured database and the query power of a structured database. A connector from the unstructured database to the structured database is required. This adds complication and cost but solves the issue. Please see summary in Table 2.

Table 2 Use Case Mapping to Database Type

Use Case	Structured Database	Unstructured	Hybrid
Row / column data (like .csv) that does not change format and needs to be queried	X		
Raw Big data that needs to be efficiently stored – like simulation or test datasets		X	
Small data with many tags that needs to be queried	X		
Big Data with many data tags which needs to be queried			X

4 Going forward

4.1 Data Management Solution Overview

Based on our survey analysis and proposal, data is a foundational part of any solution. At a high level, a possible solution for data management is shown below in Figure 8.

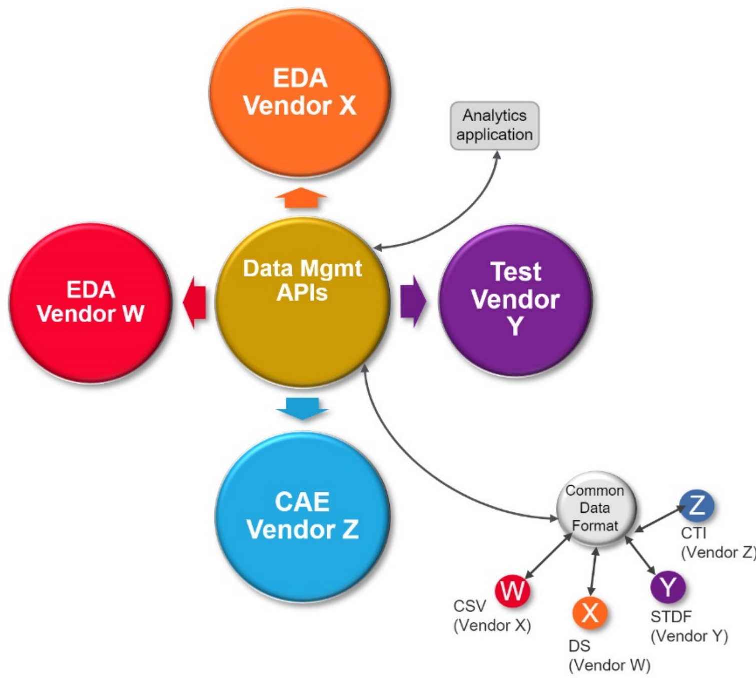

Figure 8 Data Management Solution Overview

The EDA and test vendors can contribute to the Ecosystem by doing the following.

1. Provide support to export in a common data format
2. Adopt open, interoperable, and documented APIs

Si2 can contribute to the Ecosystem by:

1. Developing translators or templates to translate a particular data format to HDF5 or JSON and a universal architecture for Open Access (OA) to support a hub common data format
2. Specify or develop a universal API for OA that supports the data management requirements.

4.2 Multi-vendor Data Integration Challenges

Integrating multiple functions from disparate tools/vendors is a challenge. Consider a scenario where we integrate annotated static timing data with PDN voltage droop and peak simulation switching activity as a required analysis. To compound matters, let's consider sourcing all three data types from different EDA vendors. As a side note, we acknowledge some EDA vendors may have a complete vertical solution for these annotations.

Data formatting differences can complicate a methodology to combine different annotations for a thorough analysis. Some formats may annotate only outputs while others may annotate nets only. Generating a complete assessment can be a challenge. For this example, we want to know if max switching activity occurs in the time domain with the worst-case timing slack and worst PDN voltage droop and for what duration. Teams require confidence all tools are properly working together.

Time-consuming analysis may be required to determine if gate simulation data is out of sync with the netlist, or PDN voltage droop is not complete or improperly applied with the simulation data for the timing slack paths of concern. Data discontinuity can lead to inaccurate/erroneous analysis and unnecessary design changes. In this example, teams commonly want confirmation for multiple factors such as:

- How complete was the gate sim activity on this particular netlist?
- How complete was the physical and PDN voltage annotation?
- If functional stimulus is only available from RTL simulation, are proper mapping files available to ensure complete analysis?
- How do power and performance pre-silicon and post-silicon predictions compare?

By applying the Hub and Spoke model described in Figure 8, multiple data formats can be integrated using a standard interface like OA to determine what data types are available and apply them in a common framework for advanced analysis. The Hub and Spoke model enables formats from different EDA vendors to integrate without dependencies on proprietary formats or single vendor solutions.

4.3 Recommend Si2 to start an industry working group

We recommend Si2 start an industry group to implement the hub and spoke concepts with an OpenAccess (OA) based design with support for adding/reading specified attributes, including metadata, to be used independent of a specific vendor. This would address the question - can metadata schema be standardized based on the functional domain, supported in OA, and leveraged across multiple tools for the end users? Vendors would create value by generating metadata for the OA schema. Also needed are applications and tools to consume that metadata. An additional Si2 project could be adaptors for connecting to the hub. Other groups at Si2 could develop adaptors, which would support migrating data between applications.

Customers can utilize faster analysis on the schema in OA, instead of working from the full log data. We further invite anyone interested in joining this effort to contact the DMW working group at leighanne.clevenger@si2.org.

5 Appendix

5.1 Cost of Engineering for Data Management

As detailed in Section 2, a typical engineer spends 3 hours every week on average in various aspects of data processing. Let us assume that on average there are 40 engineers in a team. In a large company there are typically 18 to 20 teams. And if we further assume that there are 50 companies doing design and development (which in our mind is a very conservative estimate), then the total cost of engineering for data management could be derived as shown in Table 3.

Table 3 Cost of Engineering for Data Management

Work Item	**Cost**
# of hours spent by a typical engineer per week	3
# hours spent in DMW tasks by 40 engineers (= 3*40)	120 hrs/week
# of work weeks in a year	50
Workload for a team of 40 engineers (= 120 * 50 / 2000)	3 person years
# of Teams In a large Company (assumption)	20 teams
# of companies doing design / development work	50
Estimated annual engineering cost for Industry	**$750M**

5.2 Survey Questions

If you are interested in sharing your views on these (which would be highly appreciated by this team), please contact Si2: leighanne.clevenger@si2.org.

Introduction

Welcome to the Data Management and Workflows Survey!

The Si2 TITAN Data Management & Workflows Satellite has developed the following questions to identify pain points and prioritize solution generation to improve data management and workflows in semiconductor design. As such, please feel free to forward this survey to your colleagues and friends in the industry.

Please answer the following questions thoughtfully, and to the best of your ability.

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* What is your primary professional background?

- ○ Digital design engineer
- ○ RF/analog design engineer
- ○ Board/system engineer
- ○ Test engineer
- ○ Project manager
- ○ EDA software developer

In your view, what is the top trend driving the need for better data management?

- ○ Product complexity
- ○ IP reuse
- ○ Regulatory and standards compliance
- ○ Cloud based computing

In which of the following workflows do you see the greatest challenges in product development data management? Select up to three (3).

- ☐ Requirements and program management
- ☐ Design
- ☐ Test
- ☐ Manufacturing
- ☐ Verification of design and test
- ☐ Verification of test and maufacturing
- ☐ Verification of system quality (e.g., ISO 26262)

From a data traceability point of view, please rank the following in order of importance (**most critical = 1, least critical = 5).**

- [ ] Tracing requirements to process/work item/plan
- [ ] Tracing data to requirements (compliance management)
- [ ] Tracing data to a process
- [ ] Accessing metadata to enable analytics to gain insights, troubleshoot, optimize
- [ ] Tracing design artifacts to drive standardization

Please rank the following in order of importance for EDA vendors to standardize **(most important = 1, least important = 5)**.

- [ ] Design IP, BOMs
- [ ] Data formats
- [ ] APIs
- [ ] Netlist/design format
- [ ] Other

Any other suggestions for standardization?

On average, how many hours per week do you (or a typical engineer on your team) spend collecting, formatting, reducing, processing, analyzing, and correlating data, as well as writing reports?

- ◯ Less than 1 hour
- ◯ 1-2 hours
- ◯ 3-5 hours
- ◯ More than 5 hours

For a typical product development cycle, how much time is required to correlate test data with simulation data?

- ◯ Less than 1 month
- ◯ 1-3 months
- ◯ More than 3 months

How many different data formats do you use?

- ◯ 1-2
- ◯ 3-5
- ◯ 6-10
- ◯ More than 10

What are the most time consuming data management tasks? Select up to three (3).

- ☐ Storing big data
- ☐ Locating and accessing the data needed
- ☐ Correlating design and test data
- ☐ Reducing, sorting, organizing data for processing
- ☐ Formatting data for processing
- ☐ Data analytics
- ☐ Data reuse
- ☐ Other (Please specify)

Please prioritize the following data management challenges in order of severity **(most severe = 1, least severe = 4)**.

- ☐ Integrating data from disparate sources
- ☐ Collecting, processing, validating data
- ☐ Complex data storage, organization, databases
- ☐ Security (authentication, access, authorization)

Please prioritize the following IP management challenges in order of severity **(most severe = 1, least severe = 4)**.

☐ Tracing data and IP and/or meta data linkage between steps in a flow

☐ Facilitation of IP reuse within teams

☐ Facilitation of IP reuse between different teams

☐ Configuration management of IP / version control

What are some other pain points you experience in managing your data?

☐

Where does your company deploy in-house tools to fill gaps in EDA or test workflows? Select up to three (3).

- ☐ Requirements management
- ☐ Simulation/test data management
- ☐ IP management
- ☐ Tool interoperability
- ☐ In-house product verification systems
- ☐ Analytics
- ☐ Custom tools

How would you rank the following challenges in your data management infrastructure?

☐ Communicating between multiple data management systems

☐ Linking geographically distributed data management systems

☐ Managing multiple data repositories

☐ Managing access and authorization systems

How valuable would each of the following be?

	Extremely		Minimally
Simulation or test data tagged with metadata	1	2	3
Simulation or test data searchable from a database	1	2	3
Data from different sources be translated into a common data format as an enabler for analysis of combined datasets	1	2	3
Version control for design IP, tools, processes	1	2	3
Process and design IP traceability	1	2	3

Which of the following workflow elements would have the biggest impact on your product development cycle time? Select up to two (2).

- ☐ Integration of tools across product development
- ☐ Ability to interchange data across tools and teams
- ☐ Increased team collaboration
- ☐ Better data analytics
- ☐ Automation of manual data management processes

Is your company willing to utilize or accept the following?

Cloud storage

Please select one for each

Cloud verification

Please select one for each

SaaS solutions

Please select one for each

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