Research Article
i-Proclaim .my
Asia Pac. j. energy environ.

AMI Data for Decision Makers and the Use of Data Analytics Approach

Mahesh Babu Pasupuleti

Data Analyst, Department of IT, Nitya Software Soluctions INC, 3100 Mowry Ave Suite 205, Fremont, CA 94538, **USA**

*Email for Correspondence: maheshbp.gs@gmail.com

Abstract

The Advanced Metering Infrastructure (AMI) analytics provide a source of real-time information not only about energy usage, but also as an indicator of various social, demographic, and economic phenomena inside a city, according to the National Electricity Information Administration. As a tool for leveraging the potential of AMI data within the applications in a Smart City, this article proposes a Data Analytics/Big Data framework applied to AMI data as presented in this study. The framework is comprised of three main components. First and foremost, the architectural perspective sets AMI within the context of the Smart Grids Architecture Model-SGAM. Second, the methodological view describes the translation of raw data into knowledge, which is represented by the DIKW hierarchy and the NIST Big Data interoperability model, among other things. The final factor that connects the two perspectives is human expertise and talents, which enable us to gain a better comprehension of the results and translate knowledge into wisdom. Our novel perspective responds to the issues that are emerging in the energy markets by including a binding element that provides assistance for the most optimal and efficient decision-making possible. We created a case study to demonstrate the functionality of our framework. It illustrates how each component of the framework for a load forecasting application at a retail electricity provider is implemented in the instance described here (REP). The Mean Absolute Percentage Error (MAPE) for certain of the REP's markets was less than 5 percent, according to the company. Aside from that, the instance illustrates what happens when the binding element is introduced, since it generates fresh development possibilities and serves as a feedback mechanism for more forceful decision-making.

Key words

Advanced Metering Infrastructure (AMI), Data Analytics, Smart Cities

10/31/2017 **Source of Support:** None,**NoConflict of Interest:** Declared

Introduction

There are now a number of research being conducted on the use of AMI data in Big Data and Data Analytics applications. However, it is clear that fractional advances do not contain a global integration of architectural components of the data life cycle or take into account a comprehensive approach in their design. Several Big Data and Data Analytic approaches have previously been defined on the one hand and are being refined (NIST, 2015). However, there exist models for the development of Smart Grids that include AMI systems as a part of the overall framework.

Consider, for example, the work developed in (Loshin, 2013), which included both topics in a framework, but only from an architectural perspective (Where and How?), rather than from a methodological one (How?) The majority of the developments found in the literature are focused on the application of methods, but they neglect some important cross-cutting architecture components, such as information security and privacy, data governance, information integration and sharing, platform scalability, the variability of the requirements, and the evolution of the data sources. Two key focuses are obvious from the foregoing: AMI as the technology for Smart Grids and Data Analytics/Big Data as methods for extracting value from the data created as a result of the AMI implementation.

We have chosen to keep the terms Data Analytics and Big Data separate for the sake of clarity. The first is concerned with the translation of raw data into useable information through the use of various algorithms and approaches (Pasupuleti, 2015a). It is the second phrase that relates to a property of the data that is being processed itself (volume, velocity, and variety). A Data Analytics program may or may not be considered "Big" depending on the data it is working with. The distinction is that, due to the nature of the source data, Big Data applications necessitate the use of significantly more complex processing systems. Nonetheless, other authors prefer to use the phrase Big Data Analytics to refer to the combination of one or the other technique with the other approach (Pasupuleti, 2015b).

The purpose of this effort is to develop, on the basis of these notions, a Data Analytics/Big Data framework for AMI data that incorporates human expertise and abilities as a binding factor. It is the human knowledge that includes architectures (where?) and methodologies (how?) for transforming and adding value to the AMI data, respectively. As a result, the Smart Grid, the company, and its customers benefit financially from this transition, in addition to meeting the demonstrated needs, which include not only technology requirements but also requirements for people training and abilities.

THE DATA ANALYTICS FRAMEWORK FOR AMI DATA

It is presented in this part an implementation architecture for integrating tools from both niches: AMI data and Data Analytics/Big Data, regardless of whether the data is labeled "Big." By including a binding element, the framework is able to suit them crosswise. These three primary components are discussed in greater detail in this section. Specifically, the first explicitly portrays AMI as an architectural approach, together with its role and implementation in the context of Smart Grids (SGAM). SGAM's second significant component is the evolution process that AMI data must go through in order to provide value at the business level, which is viewed from a methodological perspective. The final component, which is the connecting element between the two previous components, namely, human expertise and talents, is presented. This aspect provides for a deeper comprehension of the previously obtained results.

ARCHITECTURE VIEW: ADVANCED METERING INFRASTRUCTURE IN THE SMART GRID

The initial architectural element taken into consideration for the suggested framework is the same one that is used for Smart Grids, as previously stated. As a result, multiple writers offer several architectures for establishing a common framework for the development of Smart Grid applications in this context (Adusumalli, 2016a). The architecture proposed by CENELEC, on the other hand, has established itself as a standard in the context of Smart Grids around the world. The GridWise Architecture Council developed a concept that served as the inspiration for the SGAM paradigm. The concept of interoperability serves as the foundation for this approach, which is widely regarded as a critical enabler of Smart Grids (Pasupuleti, 2015c). A process's interoperability refers to the ability of two systems, whether from the same or different manufacturers, to communicate information and utilise it correctly during the course of the process' operation. In accordance with this concept, CENELEC divided the eight categories proposed by the GridWise Council into five interoperability layers, as depicted in Diagram 1. The goal of this grouping is to present an architecture that makes it easier to build use cases that are appropriate in the context of the Smart Grid environment. Each interoperability layer is briefly described in the sections below.

- This refers to the global picture that is obtained from a business perspective. This layer facilitates decision-making in the areas of new business models, business cases, and new market models, among other areas of expertise.
- The function layer refers to the functions and services that are provided, as well as the links that exist between these functions and services. Because the business layer implies functions, they must be studied in isolation from the actors and components in order to achieve the functionalities that have been presented.
- When we talk about the information layer, we are referring to the information that is shared between devices, functions, and services. Data models reflecting the semantics of information that travels across each network step are also considered in this framework.
- This layer describes the protocols and methods that allow for the interoperable flow of information between the various components of the Smart Grid system.
- A component layer refers to all of the physical components present in the context of Smart Grids, including but not limited to the actors and programs that run on them and the power assets, protective devices, and network infrastructure.

THE DIKW (DATA, INFORMATION, KNOWLEDGE, AND WISDOM) HIERARCHY

For the first time, Russel Ackoff developed the wisdom notion as a hierarchical framework to define the progression of an entity from its data character to a higher level of understanding in 1989. (Ackoff, 1999). He described the hierarchy as consisting of the following stages: data, information, knowledge, understanding, and wisdom (in his work). Several authors in the literature, on the other hand, prefer to consider understanding to be a component of knowledge (Rowley, 2007).

This structure, as well as others like it, have been generalized in the literature as the DIKW model (Data, Information, Knowledge, and Wisdom), which adheres to each of the hierarchical phases of the structure, as illustrated in Figure 1. Figure 1. Hierarchical stages of the structure.

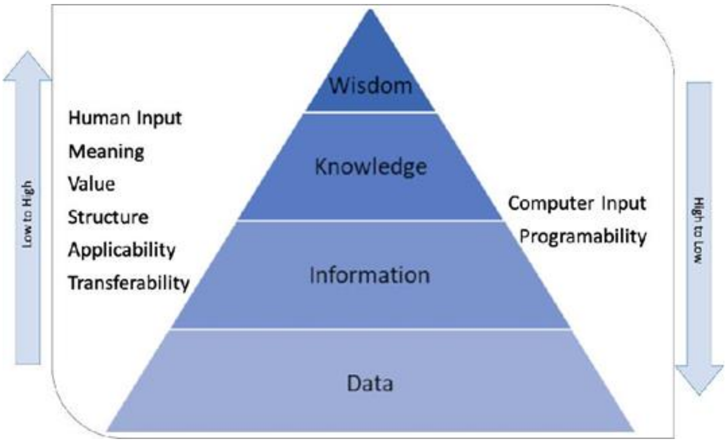

Figure 1: The hierarchy of data, information, knowledge, and wisdom (DIKW) and the shifting factors inside it.

According to the research published in (Ackoff, 1999) and the study presented later (Rowley, 2007), the following definitions are required in order to comprehend the hierarchical structure:

- Data: When we talk about data, we are referring to elemental symbols that represent the qualities of things such as objects, events, activities, or transactions. They are the result of a process of observation or measuring. However, they are devoid of any usefulness or significance.
- Information: This term refers to the data's ability to perform a function. Information is the transformation of data into a format that is understandable and meaningful in order to achieve a goal. It generally provides answers to inquiries such as "what," "who," and "when." Information systems are responsible for the generation, storage, retrieval, and processing of data. Typically, the steps of classification, rearranging/sorting, aggregation, conducting computations, and selection are necessary in order to convert data into information. The writers of (Pearlson and Saunders, 2015) emphasized the significance of the context and the purpose of the information provided in their paper.
- Knowledge: Know-how is referred to as knowledge. It is the phase that allows information to be transformed into a set of instructions. Despite the fact that there is no agreement on what it means, numerous authors assert that knowledge aids in decision-making at the most fundamental level (Pearlson and Saunders, 2015). When making decisions, it is necessary to combine common sense with semantic components that are connected to interpretation.
- Intelligence and Wisdom: Intelligence is defined as the ability to boost productivity. The ability to boost one's efficacy is defined as wisdom. The first phrase is associated with expansion (of an organization or business), and it does not necessitate the creation of additional value. Wisdom, on the other hand, implies growth, which necessitates the addition of value (Pasupuleti, 2016a). The term wisdom refers to "human judgment on important, difficult, and uncertain problems associated with the meaning and conduct of one's life (Adusumalli, 2016b)," which includes "questions associated with the meaning and conduct of one's life (Adusumalli, 2016a)." Some authors believe that wisdom is the ability to apply concepts from one domain to new situations or issues and to make more in-depth conclusions as a result of this application (Pasupuleti, 2016b).

The author of Rowley (2007) highlighted a number of transversal variables that change according to the stages of the DIKW hierarchy, as depicted in Figure 1. These variables are shown in the table below. According to the graph, each level up the ladder necessitates the development of more human talents in order to transform information and give it value (knowledge and wisdom). On the contrary, taking one step back demonstrates the necessity for computational assistance (information and data).

THE BINDING ELEMENT: HUMAN EXPERTISE AND SKILLS

A component capable of translating the information obtained by AMI data into a much more complicated and valuable category in the DIKW hierarchy is required for the framework. It has already been mentioned that human expertise and skills for decision-making and judgment about critical judgments and actions are required throughout this final transition step. In this way, notions from one area can be applied in new circumstances with ease (Adusumalli, 2017).

So that the DIKW vision may be realized, human expertise plays a critical role in the business layer of AMI over SGAM by setting goals and objectives and transforming knowledge into wisdom, as well as in the business layer of AMI over SGAM. Figure 2 depicts this human skill as a new component that completes the proposed framework by including it.

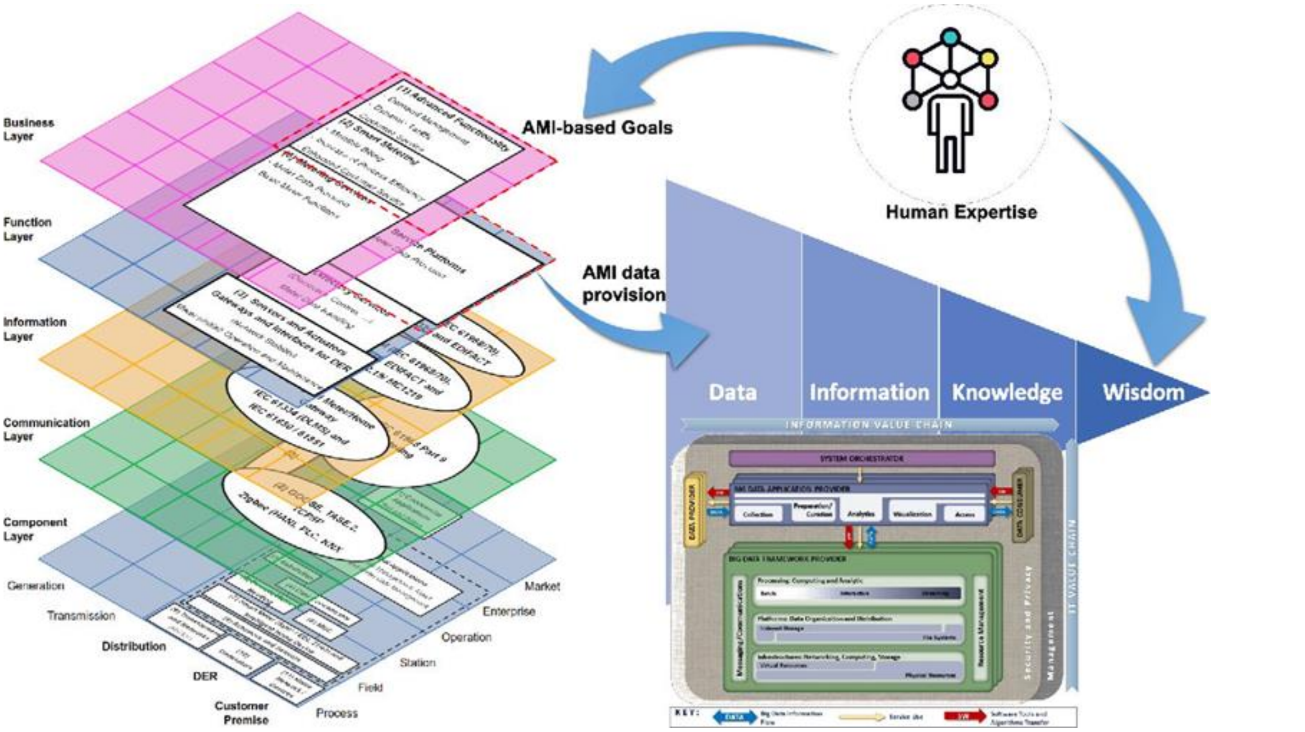

Figure 2: Data provision architecture, data evolution purpose, NIST (methodology to transform data into knowledge), and Human expertise (binding element to transform knowledge into wisdom)

West Monroe College and the Illinois Institute of Technology collaborated on a project aimed at tackling the national workforce challenge associated with the transformation of electricity grids into Smart Grids in the United States. The study concentrated on identifying the jobs that were touched by the Smart Grid and determining the extent to which the Smart Grid had an influence on these jobs. According to the findings of the study, important Smart Grid skills requirements were identified, and current training possibilities to satisfy Smart Grid workforce skill requirements were reviewed.

The team's broad knowledge was clear in the implementation of this pilot, as was their greater grasp of the results. Furthermore, the team gave the CEO with the information he needed to make a data-driven decision, which was to invest a larger sum of money in the installation of a new business platform than previously planned. Using this new business platform, the second part of this pilot would be implemented in order to obtain a more robust forecasting application that is in compliance with the CREG 100/2019 standards, which would be implemented shortly. The projected investment in this platform will have a positive impact on both the organization and the customers who would use it. Meanwhile, it will encourage collaboration between academic institutions and private energy enterprises.

Data Visualization and Access

It had divided the hourly consumption forecasts into 12-hour increments in order to provide the identical comparison scenario as before (a.m. and p.m). Because the forecast inaccuracy for some hours of the day may be compensated by other points in the same time frame, it was believed that grouping the measurements and predictions into longer time intervals would reduce the average percentage error (a-m. or p.m.). The transformation of data into knowledge through the use of data analytic tools increased the MAPE for energy consumption forecasting in 12-hour intervals disaggregated by company and market from 38 percent to 8.90 percent after applying these approaches.

In addition, we created additional dashboards that included descriptive analysis. The deployment of any data analytics or machine learning techniques is not implied by these statements. This supplementary visualization, on the other hand, was designed to make it easier for data consumers to acquire the information utilized in the case study from the data provider platform. As soon as we transform the information into knowledge, this knowledge is immediately usable and accessible to the data consumer. The data consumers in this case study are the development department of the REP as well as the company's CEO.

TRANSFORMATION OF KNOWLEDGE INTO WISDOM

Because of the stages in the framework that have been completed so far, the primary aim initially defined in the case study can be achieved: increasing demand forecasting at 12-hour intervals for a REP, disaggregated by market. However, the capabilities and expertise of the REP development team as well as our research department enabled us to take the project one step beyond. It was interdisciplinary training that was provided to personnel from both the REP and our research group. As a result, in addition to having programming and algorithm implementation capabilities (DIKW hierarchy + NIST framework), we also understood the global environment in which a REP operated inside the power grid (SGAM). In addition to being familiar with the operation, REP's supervisors were also up to date on the most recent legislation governing the country's electrical industry. On a daily basis, each REP should present their projections for each 12-hour period of the day. Their greatest prediction error each interval is 4 percent, and their maximum prediction error per interval is 4 percent. In the alternative, XM could punish the REP based on the error measure used in the demand forecasts of the respective market. In this team, we can see how the elements included correspond to the positions that require greater knowledge to provide decision support: executives, supervisors, engineers, and information technology teams.. In certain specific aspects of a Smart Grid, such as in this case, informed decision-making, the level of competence/expertise of crucial jobs is extremely important, which explains why. Figure 1 illustrates how, at these higher levels of abstraction, human judgment generated from experience and a broad context (both technological and business) has greater value than the early transformations of raw data, which are where the majority of the workload is concentrated. The emphasis is unambiguously on the computing infrastructure.

With the help of the case study offered in this research, Figure 3 compares and contrasts each part of the framework illustrated in Figure 2. The relationship of each stage on the proposed framework is indicated by gray arrows on the diagram. A pilot project for load forecasting based on data from smart meters was initially defined by the REP team as the ultimate goal of the project. In the SGAM business layer, this aim relates to a goal of the same name.

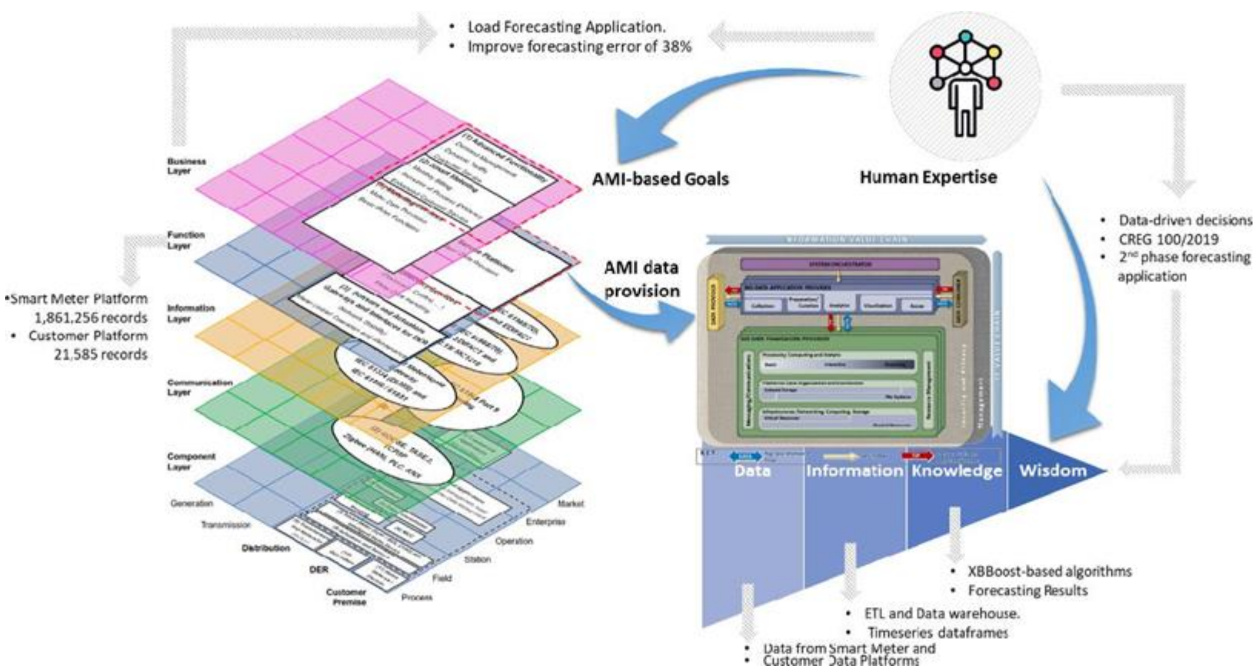

Figure 3: The phases of the case study planned on the proposed Data Analytics framework.

The knowledge and abilities of the human team were sufficient to make these high-level decisions at the corporate level. As we discussed in previous sections, the ability to apply concepts from one domain to new situations or problems allowed for the transformation of knowledge into wisdom and the making of informed decisions that benefit the REP's work in a broader context, as well as the transformation of knowledge into wisdom and informed decisions. The smart meter and customer data platforms served as data sources for the SGAM function layer, which was implemented as a function layer. The same data source serves as the initial input to the DIKW structure. We used Tableau dashboards to make it easier for end-users to get their hands on the results. Finally, we were able to gain a better grasp of the benefits of this application as well as the potential consequences of new electrical sector laws as a result of the team's human expertise and skills. In the second phase of the pilot project, this gained wisdom enabled the participants to make educated judgments on making fresh investments to expand the REP's analysis platforms, which allowed them to achieve success.

CONCLUSIONS

According to the literature, a number of writers have investigated Big Data/Data Analytics in AMI and Smart Grid applications. Some of them provided various methodologies and methods for performing data transformation, while others proposed nothing at all. In contrast, the vast majority of the studies simply achieved data analysis (methods) for a single goal, such as load forecasting or loss detection, without any connection to the global view described by SGAM (architecture). It is because of this lack of connection that, while such works accomplish the purpose of transforming raw data into knowledge, they fall short of achieving wisdom, in that the results are not always applied to new domains or situations in order to make more in-depth decisions. The most significant contribution of this research is a paradigm that enables for the progression from raw AMI data to applied wisdom in various areas of a Smart Grid over time. An architecture for the deployment of AMI in the context of Smart Grids is provided first, and from this architecture, business goals can be defined at the highest level, all the way down to the physical components required for AMI operation. The second perspective is a technical view of AMI in the context of Smart Grids; from this perspective, a technical view of AMI in the context of Smart Grids is provided. In accordance with the design, a level of access to platforms that serve as a source of AMI data has been established. The second point of view is concerned with the transformation of the AMI data. This transformation entails the application of Big Data/Data Analytics techniques and their life cycle in order to add value to the data and transform it into knowledge utilizing the various ways that are accessible. Finally, in the third perspective, human expertise and talents are introduced as a unifying element of the system. When combined with human judgment, logic, and higher levels of understanding, this is the final evolutionary step from knowledge to wisdom. As a result of this improved transformation, the worth of advancements including AMI data is increased. For the next generation of electrical networks to obtain such a deep understanding of Smart Grid processes, diverse teams will be required to operate together. In the same way, a better knowledge will enable for more informed decision-making with a worldwide impact that will benefit multiple Smart Grid value chain linkages. Further improvements to the results of this application will be achieved by future investments in the transformation of raw data into wisdom. Finally, with the help of the team's human expertise and abilities, we were able to gain a better grasp of the benefits of this application as well as its potential impact on future legislation in the electrical sector. Because of the assistance that our team was able to provide, this human judgment was the result of our ability to make an informed choice.

REFERENCES

Ackoff, R. (1999). From Data to Wisdom. In Ackoff's Best: His Classic Writings on Management; John Willey & Sons: Hoboken, NJ, USA, 170–172.

Adusumalli, H. P. (2016a). Digitization in Production: A Timely Opportunity. *Engineering International*, *4*(2), 73-78. https://doi.org/10.18034/ei.v4i2.595

Adusumalli, H. P. (2016b). How Big Data is Driving Digital Transformation?. *ABC Journal of Advanced Research*, *5*(2), 131-138. https://doi.org/10.18034/abcjar.v5i2.616

Adusumalli, H. P. (2017). Mobile Application Development through Design-based Investigation. *International Journal of Reciprocal Symmetry and Physical Sciences*, *4*, 14–19. Retrieved from https://upright.pub/index.php/ijrsps/article/view/58

Loshin, D. (2013). Big Data Analytics—From Strategic Planning to Enterprise Integration with Tools, Techniques, NoSQL, and Graph; Morgan Kaufmann: Boston, MA, USA.

NIST. (2015). NIST Big Data Interoperability Framework: Volume 1, Definitions. In NIST Special Publication 1500-1; NIST Big Data Public Working Group: Gaithersburg, MD, USA, 2015; Volume 1, p. 32.

Pasupuleti, M. B. (2015a). Data Science: The Sexiest Job in this Century. *International Journal of Reciprocal Symmetry and Physical Sciences*, *2*, 8–11. Retrieved from https://upright.pub/index.php/ijrsps/article/view/56

Pasupuleti, M. B. (2015b). Problems from the Past, Problems from the Future, and Data Science Solutions. *ABC Journal of Advanced Research*, *4*(2), 153-160. https://doi.org/10.18034/abcjar.v4i2.614

Pasupuleti, M. B. (2015c). Stimulating Statistics in the Epoch of Data-Driven Innovations and Data Science. *Asian Journal of Applied Science and Engineering*, *4*, 251–254. Retrieved from https://upright.pub/index.php/ajase/article/view/55

Pasupuleti, M. B. (2016a). The Use of Big Data Analytics in Medical Applications. *Malaysian Journal of Medical and Biological Research*, *3*(2), 111-116. https://doi.org/10.18034/mjmbr.v3i2.615

Pasupuleti, M. B. (2016b). Data Scientist Careers: Applied Orientation for the Beginners. *Global Disclosure of Economics and Business*, *5*(2), 125-132. https://doi.org/10.18034/gdeb.v5i2.617

Pearlson, K. E., Saunders, C. S. (2015). Managing and Using Information Systems: A Strategic Approach, 6th ed.; John Wiley & Sons: Hoboken, NJ, USA.

Rowley, J. (2007). The wisdom hierarchy: Representations of the DIKW hierarchy. *J. Inf. Sci.*, *33*, 163–180.

--0--