PLANNING MALAYSIA:
Journal of the Malaysian Institute of Planners
VOLUME 19 ISSUE 3 (2021), Page 423 – 437

BIG DATA ANALYTICS FOR PREVENTIVE MAINTENANCE MANAGEMENT

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Abstract

Maintenance data for government buildings in Putrajaya, Malaysia, consists of a vast volume of data that is divided into different classes based on the functions of the maintenance tasks. As a result, multiple interactions from stakeholders and customers are required. This necessitates the collection of data that is specific to the stakeholders and customers. Big data can also forecast for predictive maintenance purposes in maintenance management. The current data practise relies solely on well-structured statistical data, resulting in static analysis and findings. Predictive maintenance under the Big Data idea will also use non-visible data such as social media and web search queries, which is a novel way to use Big Data analytics. The metamodel technique will be used in this study to evaluate the predictive maintenance model and faulty events in order to verify that the asset, facilities, and buildings are in excellent working order utilising systematic maintenance analytics. The metamodel method proposed a predictive maintenance procedure in Putrajaya by utilising the big data idea for maintenance management data.

***Keyword**:* Big data, analytics, maintenance, forecasting, Malaysia

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INTRODUCTION

Building maintenance management is an issue that must be handled at every stage of the construction process. Buildings must be maintained on a regular basis, and in most nations, building maintenance is a substantial undertaking (Horner et al. 1997). In reality, it plays a role in the company's long-term success. Because of the consequences of a building without facilities and maintenance, maintenance management and asset management work closely together. Human intervention has recently resulted in the production of a large amount of data. This data, especially for the government, must be treated with extreme caution, since it is a critical component for top management in making successful and informed decisions based on true data and information. Big data refers to the phenomena of massive amounts of data growing at a rapid rate and in a variety of formats, both structured and unstructured.

Preventive maintenance is crucial in maintenance management because it protects the good state of facilities before they fail. Once the method is implemented, a considerable amount of data about operation and maintenance will be generated. JKR is responsible for the preservation of government and asset maintenance data in Malaysia; nevertheless, this is a problem because the stored data is vast and underutilised. The analysis of this data is critical for better decision-making. Furthermore, although much Big Data (BD) has been undertaken in Malaysian business, particularly the government, it is not used in the maintenance management of government facilities. Aside from that, numerous Information and Communications Technologies (ICTs) are suggested for use in the industrial realm; however, this does not provide a comprehensive picture of the BD method. Most organisations nowadays rely on computer-assisted services, including maintenance management. Normally, this assistance comes in the form of a decision-making mechanism. Eventually, this will contribute to the organization's overall efficiency. Poorly maintained resources can cause a company's operations to come to a halt and result in a loss of revenue. Maintenance management actors must re-orient themselves as globalisation and shifts in information and communication technology increase (Dixon 2007). (Razali & Juanil 2011).

Despite the fact that mySPATA was created to make data collection of government building assets and maintenance data easier, it is currently unavailable due to system integration involving a large amount of data. The system is attempting to adopt Business Intelligence (BI), but so far it has been unsuccessful. According to JPAK (2014), there has been poor record management, non-centralized information that has not been updated to mySPATA, and hence there are concerns that need to be addressed. Furthermore, whether CMMS and mySPATA are useful in assisting senior management in making decisions about the assets and maintenance of government buildings in

Putrajaya is a significant question. The data contained in the Computerised Maintenance Management System (CMMS) is still incomplete for analysis and projection to aid or support strategic decisions in the management of facilities, according to the research and monitoring done. Although it is capable of producing dynamic dashboards for decision-making, it does not use BI to provide real-time analysis or an interactive dashboard to the user, making the system easier to grasp for beginners. With the rise of BD and the advancement of smart technology, an organisation can use 'business intelligence' to modify its daily operations in a more intelligent manner (BI). Property players can benefit from BI because it keeps them more informed, which helps them make better decisions. People's high expectations for real-time analysis are critical. It enables governments to make choices more quickly and to monitor them in real time. With the usage of smart technologies, BD plays a larger role in acquiring and analysing data, while BI assists the maintenance department in making educated decisions. Due to issues occurring in the administration of government building maintenance, particularly during the decision-making stage, the research to be conducted is critical. Maintenance data that is scattered, insufficient, and inaccurate has become a burden for the maintenance department, making modelling the process or managing maintenance activities extremely difficult and complex.

LITERATURE REVIEW

BD has evolved into a new field that necessitates the collection of data and the integration of data systems. Academic and professional professionals have been drawn to the evolution of BD. This area highlights the most recent advancements in the world of electronic commerce today. The industry's top buzzword is BD (Waller & Fawcett 2013). The application of BD in corporate decision-making and enhancing efficiency has also been demonstrated in Malaysia's commercial industry. Companies, academia, and the business press have been drawn to a quantitative information explosion caused by human behaviour on the internet and social media. Roger Mouglas of O'Reilly Media coined this term in 2005 (Beebe 2019), a year after the business coined the term Web 2.0. The term BD was coined by Mouglas to describe reference datasets that are too vast to be analysed and handled using typical BI techniques. Traditional data-processing systems can no longer handle massive volumes of data, necessitating the development of new technology (Provost & Fawcett 2013). This is referred to as BD. BD has become a buzzword that has been used in a variety of industries around the world. Despite the fact that the genuine benefit of BD is unknown (Boyd & Crawford 2012; Desouza & Jacob 2017), analysts have noticed that BD solutions have been marketed as a means of focusing on public issues (Desouza & Jacob 2017).

Governments can benefit from BD in a variety of ways, including cost savings, improved services, and occupancy insights. The real estate data can be utilised to provide valuable recommendations to top officials, administrators, and the general public about how facilities are used, how efficiently assets are operated, and how to anticipate possible liabilities and possibilities ahead of time. A complicated portfolio of different sites, construction kinds, and oversights might also benefit from centralised information. Because buildings may be centrally owned and operated or leased by different agencies and departments, viewing the big picture can be difficult for many governments. A centralised data management system can provide cost-saving insights and innovative methods to serve constituents, as well as inform typical buy, sell, lease, and occupancy decisions. The effort will make it easier to put land to its best and greatest use, opening up new development possibilities (CBRE 2018).

Predictive analytics can be used to forecast future events, such as real estate requirements and expected staff growth or reductions as a result of public policy efforts. Another major problem is determining where different departments and individuals will be most productive and collaborative. The potential benefit of co-locating agencies that serve the same constituents or operations can be shown via BD insights. According to CBRE (2018), combining counter-parties with BD analytics allows for more efficient resource allocation, resulting in savings for homeowners who have more options. The impact of BD on supply networks will be enormous. BD will support a change from production-led supply chain management to consumer-centric demand chain management by improving visibility of end-customer demand or offering insight into future demand. This is more than a semantic shift; it will shift the focus away from the supply of items pushed out to markets and toward the demand for products, better connecting producers and customers. One method to get around this is to use open-source software. Essentially, organisations can start to rely on open-sourcing by exposing the source code of their software, allowing users and staff to change programmes and apps to improve connection inside their processes. It is believed that BD will be able to provide data management solutions that range from a simple repository to an open-source solution. BD has the potential to be used in the future to manage knowledge, particularly for governments handling building maintenance data. Governments have begun to use BD to assist in making real-time choices and expanding in-motion, according to Kim et al. (2014). He went on to say that government decision-making typically takes longer and involves a variety of stakeholders, including officials, interest groups, and individuals. As a result, BD seeks to make quick judgments with a small number of players. According to the findings of the investigation, BD will create extremely relevant data that will assist management in making better decisions.

METHODOLOGY

Putrajaya was chosen as the research region since it is the seat of Malaysia's new federal government. It's in the middle of a multimedia corridor. Many government buildings and ministries are located in Putrajaya, Malaysia. Putrajaya is an excellent location for performing this study because it focuses on government buildings.

This study employed a metamodeling approach to collect maintenance data in order to give it more structure and to make it more complete. It would be fascinating to learn how a BI application in the form of a metamodeling approach may make Malaysian building maintenance management methods more realistic without requiring a large crew. It also allows maintenance managers to make quick judgments based on more structured data in a short amount of time. According to Thompson (2004), BI enables for faster and more accurate reporting by as much as 81 percent, with 78 percent enhanced decision-making, 56 percent improved customer service, and 49 percent more income. As a result, a large number of BI applications have been implemented in a range of fields, and the field is considered to be rapidly evolving (Aruldoss et al. 2014).

Metamodeling is a technique for generating properties for a model of a model (Sprinkle et al. 2010). A domain metamodel will be created using the metamodeling approach. The metamodeling technique is effective in situations when there is a lot of information that isn't properly organised, such as in emerging fields like maintenance management. Metamodeling, according to Othman (2013), is an artefact that can represent the modelling language that describes all of the constituents in a model. A metamodeling approach might combine different domain models to create a metamodel for the domain that generates the abstraction. It includes a list of themes (issues) as well as a diagram illustrating the relationships between the concepts. The data in this situation pertains to maintenance management.

Some refer to the metamodel as a model of model, whereas it is actually the model's explanation. When the model is the subject's representation, or, in other words, the real-world problem, the metamodel is the explanation of the subject's model (Völter et al. 2013). According to Susi et al. (2005), a metamodel is a set of possible instantiations in some modelling languages that are all and only syntactically correct models. It is possible to change and reuse the metamodel for specialised needs. Metamodel is also known as a domain model glossary since it collects all of the properties from multiple sources to serve as a language for domain metamodels. As a result, the model is easy to grasp and is developed by domain experts, which may aid in the development of a system that is not reliant on technology expertise. As demonstrated in Figure 1, this will result in a viable and efficient system as well as encourage information sharing among domain experts. The subject of a real-world problem is to manage maintenance management data in the case of maintenance management data. As mentioned in the previous section, Putrajaya's maintenance data is still mostly managed manually. As a result, the metamodel notion was adopted as a solution to turn data management into a systematic process.

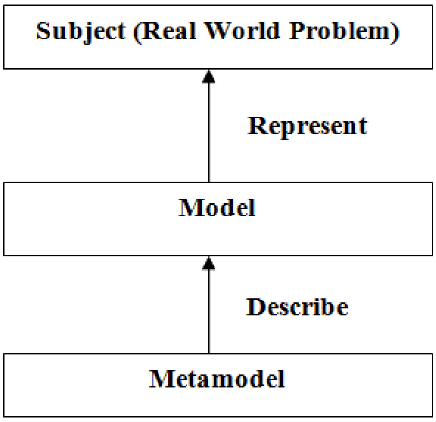

Figure 1: Subject, model, and metamodel relationship
Source: *Völter et al. (2013)*

BIG DATA IN MAINTENANCE MANAGEMENT

The maintenance manager should have complete information on maintenance data before making a judgement on a building's maintenance. The vendors, who are under JKR's management, have access to all maintenance data in the Putrajaya Federal Government Office Building, which includes mechanical, electrical, civil, housekeeping, landscaping, and pest control services. Each ministry building in Putrajaya typically has a single facilities management business that oversees services such as mechanical, electrical, civil, and landscaping. The work process for government-owned property assets is very transparent and organised at the structural level. Nonetheless, property asset management should never be viewed as an afterthought in the growth process, but rather as a systematic approach to a specific goal. The government mostly regards its property assets as a tool of carrying out social and regulatory tasks, rather than recognising the properties' inherent value. The current property administration of government buildings in Malaysia is more akin to maintenance management, according to the popular consensus. According to a prior study by Razak (2010), the majority of ministry buildings are not involved in the property's complete existence. Due to the process including both data management and processing, one of the biggest problems for maintenance management is transforming data into usable information to assist predictive analytics. Because of the large number of buildings and job tasks in maintenance, there is a difficulty in terms of data expansion, processing analytics, and decision tree analysis. Few scholars have looked at big data from the perspective of maintenance management since its inception. As a result, when complex interactions and nonlinearities are present in dataset models in maintenance management systems, it is influenced in terms of practical constraints in developing statistical methodologies. The goal of predictive maintenance is to infer all duties related to civil works based on the technician's inspection and data records, which are then validated by the superior. As a result, understanding how to predict civil works is crucial. For example, understanding the asset condition lifespan, also known as lifecycle assessment (LCA), for each asset in a building is critical. A predictive model, such as regression analysis, can usually anticipate the assets' lifespan state. In order to anticipate future failures, the model can examine the variables and conditions that contributed to previous failures. Predictive analytics technology was utilised to create data-driven models of specific assets using machine-learning algorithms. As a result, maintenance staff must be well-versed in statistics, modelling, machine learning, and data mining in order for the big data system in maintenance management to function at its best.

BIG DATA PREDICTIVE MAINTENANCE SYSTEM BY USING THE METAMODEL METHOD

Before the construction of the Building Metamodel (BMM) metamodel began, the data for BMM was acquired by analysing prior studies of BMM variables and performing research into the concerns and obstacles that affect BMM performance. The methods listed below were carried out in order to establish the Building Maintenance Metamodel (BMM) framework.

a) Identifying the major factors
Building maintenance management factors were gathered before the development in order to discover the source, issue, and challenges that produced the problem in the existing domain.

b) Candidate shortlisting definition
Following the extraction of the BMM factor from the acquired data, the definition of each of the factors will be presented in order to group the factors into a common meaning for BMM.

c) Definitions must be reconciled
Following the determination of the BMM determinant, the procedure for maintaining the common definition specified earlier in order to create the metamodel will be followed.

d) Factor designation
The group of factors for BMM can be split into distinct sets of views when the various groupings of the factor are completed.

e) Identifying Relationships
After determining the BMM factor, the relationship between the factor and the sub-factors will be examined and validated in order to establish a link or connection between the factors.

f) Metamodel Creation
The building of a BMM metamodel will begin after recognising the factors of BMM and their relationships. The model will be drawn using tools such as Microsoft Visio. During this procedure, the metamodel's class, entity, attributes, and operation will be incorporated.

g) The Metamodel's Validation
This stage will be completed after the factor and its connection have been developed in the metamodel. This stage is critical in the BMM metamodel design process because it determines whether the component is consistent, well-presented, and coherent in relation to the listed objectives. is that the relic provided by DSR must be fully described, formally talked to, aware, and consistent on the inside (von Alan et al., 2004). As a result, the model necessitates metamodel validation. In this phase, two strategies will be used:

i. Frequency-based Selection is a technique for confirming the accuracy of inferred ideas' beginnings and examining any missing concepts from the domain models being studied in the early stages of the first BMM's development.
ii. Face Validity is a research method in which the developer interviews experts in the topic.

The development will begin with the extraction of generic BMM factors such as BMM determinants; next, from the materials obtained prior to the start of this research, the candidate for definition will be shortlisted and designated. The relationships between the factors will be determined after all of the factors have been defined. All of the phases will be detailed as illustrated in Figure 2 utilising the 8-Steps of Metamodeling Creation Process developed by Othman and Beydoun (2010a). The metamodel phases are described in the following method, which is based on a large data approach to BMM generation.

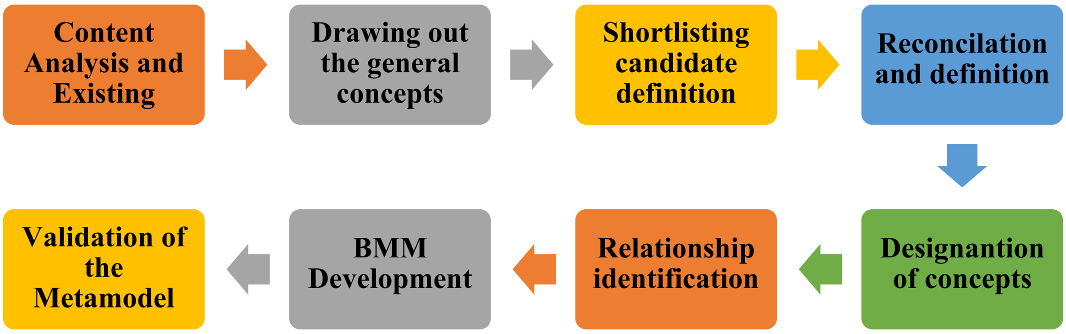

Figure 2: Steps of Creation Process BMM

Phase 1 (Figure 3) describes how governments, professionals, maintenance management units, communities, and individuals can effectively anticipate, respond to, and recover from the effects of likely, imminent, or current maintenance events or conditions using knowledge and capacities developed by them. These include a maintenance plan that involves practising, generating, documenting, and updating responses as well as technical plans for all of their components. The Descriptive Analytics Model (DAM) highlights fundamental concepts in government building maintenance management. Contractors, the federal government, property data, regulations and guidelines, buildings and land all play key roles in descriptive analytics, regardless of the type of data (textual and non-textual). To mitigate data into business intelligence processes, all of these actors must collect and combine all objectives, measurements, and software types (Unit 1, Unit 2 and Unit 3).

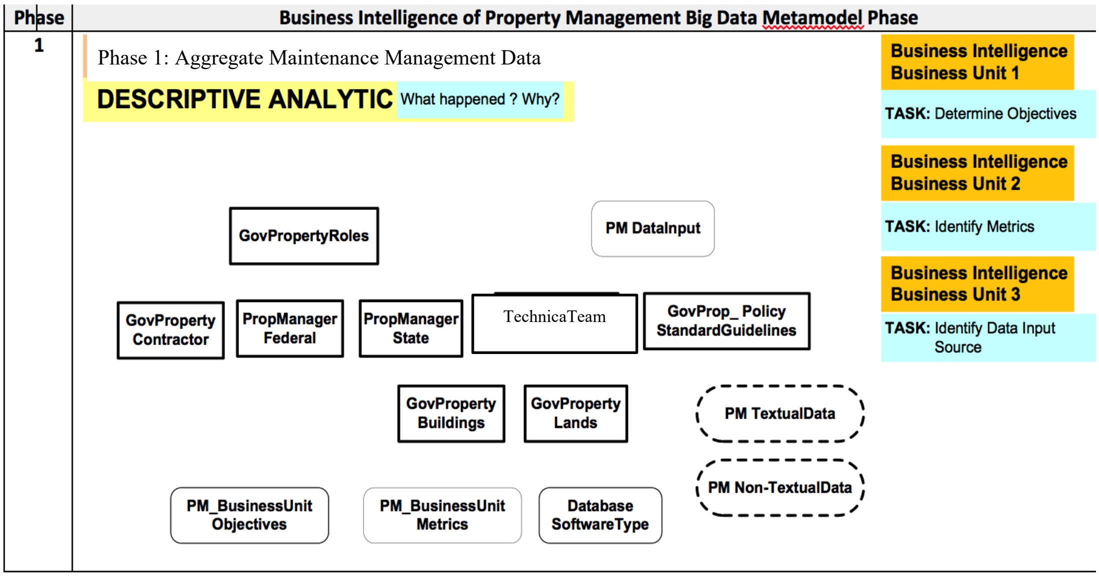

Figure 3: Phase 1: Aggregate Maintenance Management Data

Phase 2 (Figure 4) contains current maintenance management data, which includes "Government property roles," "Maintenance management data input," "Maintenance management dashboard," "Business intelligence tools," "Database software ready," and "Maintenance management business unit objectives," among other major actors. Within the maintenance management data repository system, these pieces are still connected.

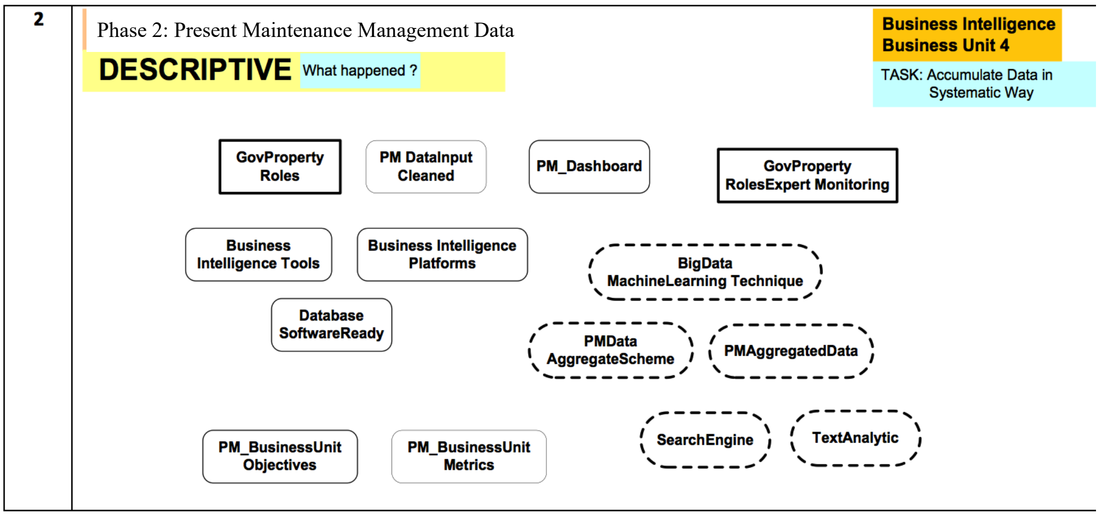

Figure 4: Phase 2: Present Maintenance Management Data

Phase 3 (Figure 5) is dubbed "Enrich Maintenance Management Data" and consists of a number of tools aimed at boosting the use of big data analytics in maintenance management, including artificial intelligence, automation, and predictive analysis. This entails the use of human resources, with government asset consultants tasked with identifying real issues with the asset upkeep management of government buildings in Putrajaya. As a result, it will start the following phase, such as data visualisation preparation, data visualisation validation, real problem data for government buildings and assets, and error handling operations. This phase's output process will be able to provide a variety of user interfaces, such as data visualisation. All of these procedures necessitate IT system integration, which involves all prior process stakeholders.

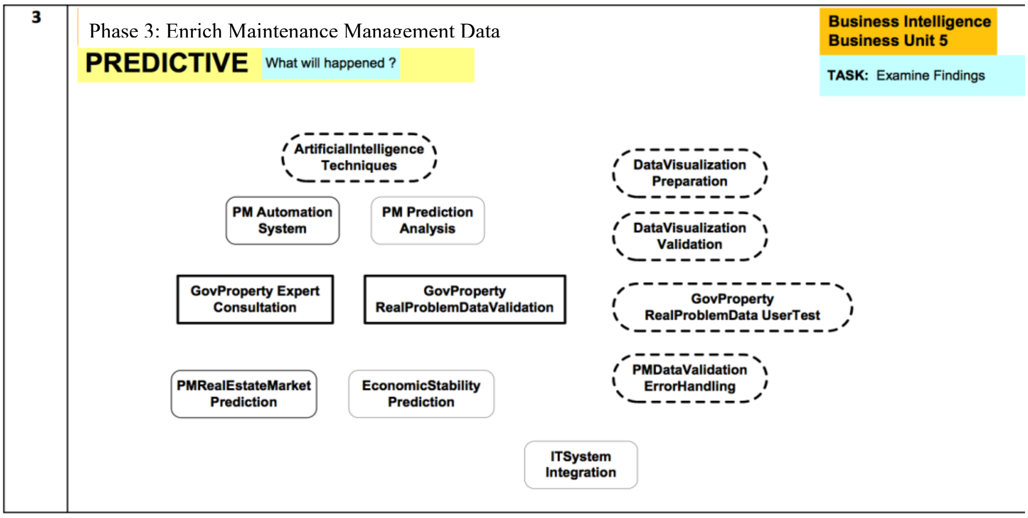

Figure 5: Phase 3: Enrich Maintenance Management Data

Phase 4 (Figure 6) focuses on "Inform Maintenance Management Decisions," and the role of all stakeholders in the maintenance management process is critical. This is where all of the data has been organised and is ready to utilise, resulting in the "Big Data Business Intelligence Results" domain. The application of "Artificial Intelligence Techniques" will improve the upkeep of large data analytics systems. Stakeholders can develop reports and forecasts of outputs in this phase, which can be utilised to make financial decisions about maintenance management. Users can use the outcome for strategic decision-making in organisations based on the objectives and matrix during this phase.

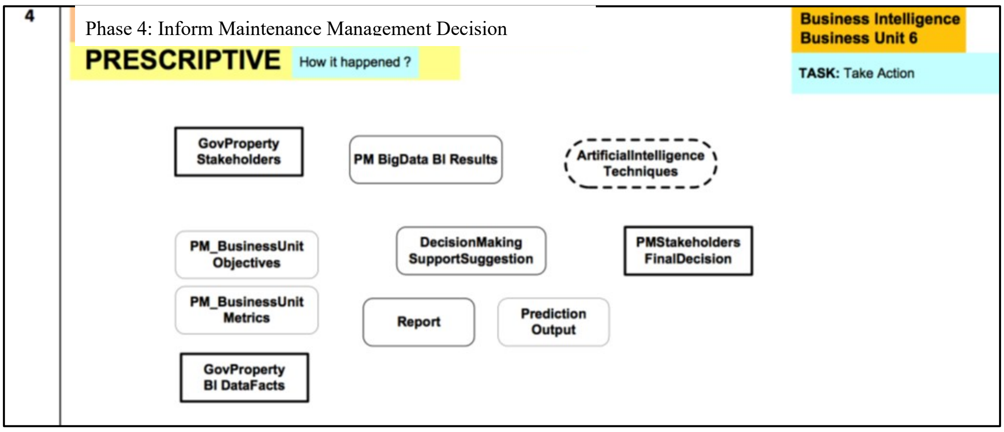

Figure 6: Phase 4: Inform Maintenance Management Decision

Figure 7 illustrates the overall structure of the system. In this system, the data is acquired from various resources which is extracted from all vendors involved in maintenance management. The architecture of the predictive maintenance system is derived from the metamodel method.

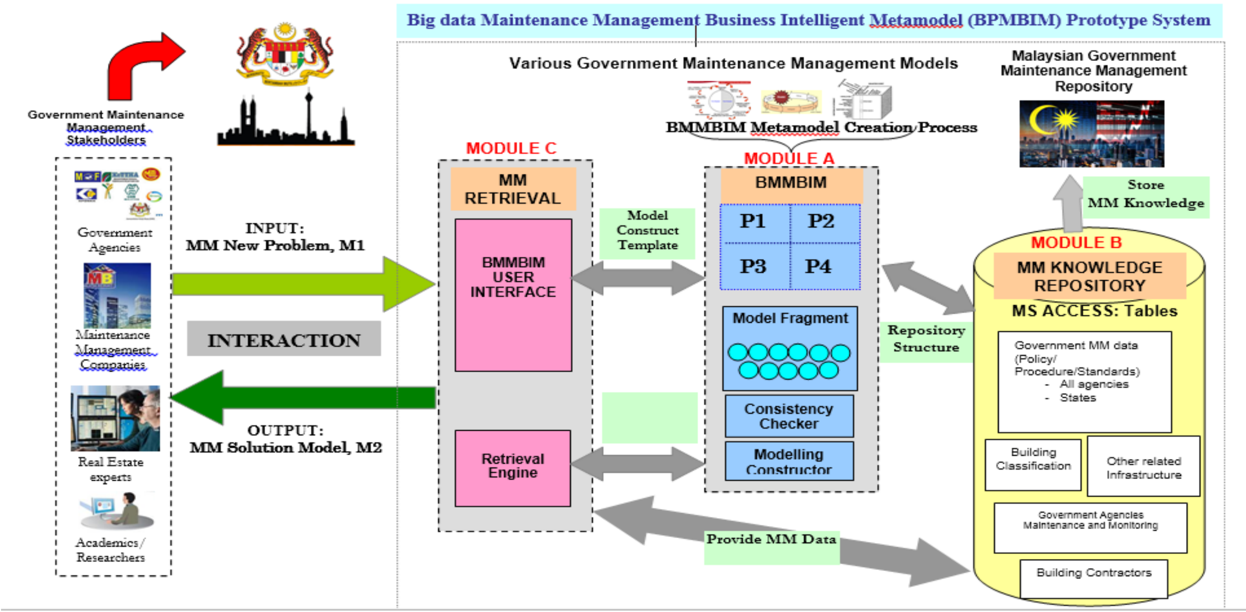

Figure 7: Big Data Analytics' Architecture for Maintenance

CONCLUSIONS

Building upkeep is an issue that must be addressed at every stage of the property life cycle. Buildings must be maintained on a regular basis, and in most nations, building maintenance is a substantial undertaking. The massive amount of public property created as countries evolve over time has necessitated the implementation of systematic maintenance management systems. These properties must be handled in a methodical manner, as property management generates revenue for the government. Existing buildings' functionalities can be preserved and tenants' demands met through appropriate maintenance techniques. This approach, however, has not been explicitly or consistently emphasised. There have been several reports of faults in public structures. This is especially true in Putrajaya, which is home to government offices. Government offices must be well-maintained not only for the sake of the country's image, but also to ensure that the government can govern successfully. As a result of this problem, it is necessary to manage government properties in a methodical manner, with proper databases of maintenance data. This information may be easily transmitted to users for decision-making, resulting in well-structured knowledge. As a result, the goal of this research is to discover characteristics in BD apps that can be used to produce maintenance management data for federal government buildings. Using Business Intelligence (BI) methodologies in the form of a metamodel framework, this study seeks to offer a novel strategy to managing a fragmented and complicated domain structure. The metamodeling technique can help stakeholders in the maintenance management domain (government, Public Works Department, facilities manager) comprehend and guide them through the decision-making process in the future. Importantly, the metamodel provides a comprehensive structure of general principles and best practises for distinct collections of maintenance management improvement models. If the metamodel-based repository system is established and disseminated, the study will be valuable to the government, particularly policymakers and auditors for decision–making. As a result, maintenance management metamodels promote information sharing and, more crucially, maintenance management in federal government facilities. Systematic management of infrastructure and properties, particularly those under government control, will benefit governments.

ACKNOWLEDGEMENT

The authors would like to express gratitude and appreciation for the research grant funding under National Property Research Coordinator (NAPREC) Vot 17H05 Number and UTM for the financial support in this research.

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Received: 12th July 2021. Accepted: 7th Sept 2021

