Towards Big Data and Internet of Things as Key Aspects of Energy Efficiency

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***Abstract* – In the energy industry, smart metering and sensor technology provides access to unprecedented amount of information, thus rapidly expanding a dissimilar and compound big set of data which is handled by the Energy Management Systems. This manuscript per the authors presents a generic architecture of Energy Management System suited to handle structured, semi-structured and unstructured data, coming from various sources in a heterogeneous workload. The paper focuses on the main operational subsystems and the database management challenge in the Internet of Things.**

***Keywords* – Energy management system, Generic architecture, Database management issues, Consumer behaviour model.**

1. Introduction

The availability and affordability of sensing and transmitting devices to monitor the energy usage in premises have met an improvement over the last few years. Many manufacturers, vendors and power utility companies engage in manufacturing and promoting different energy consumption monitoring devices in order to increase the awareness of the importance of smart energy use [36]. In the energy industries, devices like smart meters are able to collect a large amount of structured data. Integrating this data and transforming it to useful information for decision making and analysis is a challenge. Whereas structured data can be less complex to collect, unstructured data that encompasses volume, velocity and variety can be complicated to manage [22], [23]. Involved here are substantial number of various devices collaborating with each other and the real world, assessing and retrieving valuable information, thus assuring the stability of composite business mechanism which modern enterprises depend on [19]. The data itself has no value, unless it is turned into information which lays the base on which sound business decisions can be made and operational efficiencies can be achieved. This transformation requires people and systems which handle and translate the data into a meaningful knowledge. Smart metering and sensor technology provides access to unprecedented amount of information that can forecasts energy usage, detects fraud, predicts maintenance requirements and leads to smart grid integration which can intelligently monitor supply and demand variations [9], [39], [44]. This excessive growth of heterogeneous and complex big data signals for immediate adjustment of the way information is processed in the distribution systems. Otherwise, decision makers are fated to face a huge challenge caused by Data overload. Most popular computer and web applications are already powered by big data analytics algorithms [3], [47].

Life can become more comfortable by placing actuators and sensors in the buildings. For instance, room heating can be adapted to the weather and our preferences; room lighting can be changed according to the time of the day; alarm systems and proper monitoring can be used to prevent incidents in the household; automatically turning off the power of the unused electrical equipment, thus saving energy [2]. Since the enormous quantity of generated data is a key characteristic of the Internet of Things (IoT), bringing the vision of the IoT to reality highly depends on correctly managed data [15], [45].

IoT, big data storages and analytics techniques must be combined with building energy management to deliver operation savings, as well as business

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knowledge and insights that enable better planning, marketing and financing. The main objective of the current research is to propose a flexible Energy Management System architecture, which can handle heterogeneous workloads with structured, semi-structured and unstructured data from many and dissimilar sources. To that purpose, we focus on the main operational subsystems and the challenges addressed to the database management in the IoT. The proposed architecture offers a solution for storing and retrieving sensor data in a responsive way.

The remainder of this work includes the following: Section 2 surveys some related works. In Section 3 we present brief information background about IoT and big data. A generic architecture of an Energy Management System and related database issues in the IoT are considered in Section 4. Finally, we conclude our work in Section 5.

2. Related works

Apart from key enabling technologies and application domains demanding an IoT research, the surveys presented in [2], [14], [18], [37] observe the challenge in manipulation of a very large amount of data across heterogeneous systems, as well as, the integration of these systems. Transaction handling, process modelling, indexing and querying is also examined. The authors' work underlines descriptive, historical, environmental, positional and identification data, which is diverse type of data and is part of the Internet of Things. Nevertheless, researchers still face an issue and report various visions of this IoT case by reviewing enabling technologies.

The survey presented in [4] points at consumer advantages, timing consideration, limits of computation, multi-objective scheduling, designing heterogeneous devices and forecast unpredictability as a target for the Home Management Energy Systems (HEMS). Attention is focused on the reactions and operations of these systems as an outcome of the way they are designed. Comparative analysis of HEMS is also provided.

The objective of the simulation model of household behaviour under variable prices [17] is to generate realistic, residential load profiles, which are highly correlated to empirically, historic household data of power consumption. The authors present an algorithm which simulates residential load shifting under time-of-use regimes based on previously generated profile data. The model includes diverse groups of household appliances with their technical and practical usage patterns and operation constraints, thus providing a realistic demand response behaviour.

In their work [10], Conejo et al. describe an optimization model aiming at adjusting the electricity consumption utilities to the minimum of energy consumed per day, regulating and implying limits of the minimum and maximum power load per hour. Thus, adapting the hourly load level to the hourly electricity price.

Zipperer et al. discuss [48] the ability of the smart household to reduce the carbon footprint and lower the energy bills by improving power efficiency. This is done by adding renewable resources and including the inhabitant participation. The study stresses the role of the consumer as a factor and the technologies maintaining the economical energy usage in smart homes.

The review [46] of Home heating, Ventilation and Air Conditioning (HVAC) systems, evaluates the progression and the ability of these systems to change the temperature to the preferred one by the inhabitant. This is done by sensors, tracking and learning the pattern of chosen temperatures, as well as, being able to tell the difference between occupied and unoccupied building. HVAC systems now use "intelligent" programmable thermostats but still do nothing more than turning the system on and off for they are binary implemented.

Ramakrishnan et al. present [34] a project of dynamic adaptation in a smart building in Australia. The house is equipped with solar panels, which are connected to the smart grid for distributed generation of electricity, as well as, with batteries to store the energy. This way, the management of energy is built on Web of Things which lowers the expenses and decreases emissions

A smart-grid is being developed in the University of Texas, which allows users to observe their consumption of electricity as the unused energy is sent back to the grid. Thus, the supply is based on consumers' needs therefore reducing the price for end users and providers, saving resources [5].

The work described in [33] is focused on demand management web built system pending on factors like algorithms managing the home energy, demand response web service, web Home Energy Management System security, preferred ZigBee protocol, profile characteristic interface for the devices and the inhabitant's assistance. This framework senses the peak load in the electric system and reduces it adjusting the power in the domestic devices to the user's choice.

The potential of the Digital Environment Home Energy Management System (DEHEMS) is explained in [24], [25] and [40]. This wide scale system's sensors detect the electrical circuit, devices, gas usage and temperature, thus evaluating the energy consumption in the building. DHEMES uses computerized smart infrastructure, hence by analysis and combination of the collected data, chooses the best approach to enhance power saving.

The interest in Future Internet and smart cities has recently been driven by two objectives [20], [35]. On the one hand, we have the use of new Internet technologies: networks built on sensors, smart devices, RFID, the semantic web and the Internet-of-Things, cloud computing for offering new e-services to citizens and optimizing the functioning of cities. On the other hand, there is the pursuit of sustainability as the forthcoming green cities are looking for more inclusive and sustainable future with less energy consumption and fewer CO_2 emissions. Most likely, Internet of Things is the highest vital component of the current technology shift in smart cities. IoT combines active sensors and RFID for robust and cost-effective identification of many different objects in terms of functionality, technology and application fields in cities.

3. Big data and IoT properties review

In this section, we recall the basics of big data and Internet of Things (IoT) and present an overview of the essential characteristics for their integration.

To be able to manipulate vast load of information for acceptable amount of time, big data needs innovative technologies which differ from the usual software for retrieving, collecting, managing and evaluating data [12], [27], [32], [41]. For this purpose, advanced algorithms and architectures are being developed and creative approaches are being adopted, deriving insight of essential importance.

Key aspects of big data [16], [26], [28]:

1) *Volume* – The amount of information. Minicomputers and mainframes have stored data that has its growth now risen to petabytes and is continuing to grow.
2) *Variety* – Data comes from various sources and in different form and has expanded from legacy and structured data to unstructured and semi structured, audio, video, XML, Web services etc.
3) *Velocity* – The speed the data flows to the enterprise, especially when big data is processed in real time.
4) *Veracity* – big data is sourced from multiple various places.

IoT is the way and the ability of various and different, unique addressed objects (things) to communicate between each other. These wired and wirelessly connected objects have the purpose of establishing new connections with other things (objects), thus developing advanced applications and continuing the process. In this context, the research and development challenges associated with the creation of a smart world are enormous [1], [6], [13], [30], [43]. IoT is a world of perceptive environment operating on data from digital, virtual and real sources, thus creating smart cities, energy, transport etc. (fig. 1.). Here are some specific applications in different subject areas [2], [11], [18]:

- *Home automation* – smart lighting, smart appliances, smoke/gas detectors and smart security systems;
- *Retail* – inventory management, smart payments and smart vending machines;
- *Cities* – emergency response and traffic control, smart parking, smart roads;
- *Industry* – machine diagnosis, indoor air quality;
- *Environment* – weather monitoring, air pollution monitoring, noise pollution monitoring, wildfire detection;
- *Logistics* – fleet tracking, shipment monitoring, remote vehicle diagnostics and route generation and scheduling;
- *Energy* – smart grids, renewable energy systems and fault detection;
- *Health & Life style* – people monitoring, bio sensors, remote healthcare.

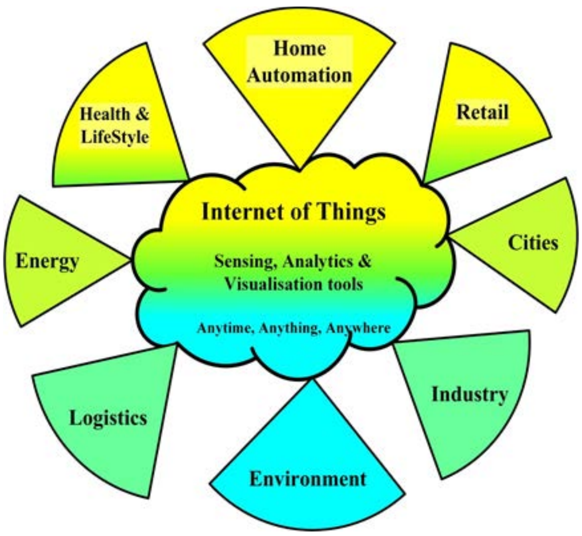

Figure 1. Internet of Things in the context of subject areas

The aim of the Internet of Things (IoT) is to enable everyday objects to be connected at any time and any place, to anything or anyone, ideally using any service and any path or network, thus making IoT the new Internet revolution [13], [38]. Major objective of the IoT is the establishment of intelligent, perceptive environments, such as self-aware climate, food, energy, mobility, digital society and healthcare. Examples include smart transport, smart products, smart cities, mart buildings, smart rural areas, smart energy, smart health, smart living etc. [31], [43].

4. A generic architecture of an Energy Management System

Figure 2. depicts the main operational subsystems of an Energy Management System. The dependencies represent the fact that one subsystem makes use of another subsystem's utilities. This system's architecture models the main subsystems and outlines the collaboration between them. The process's primary purpose is to gather and communicate power-usage data collected from multiple buildings (private or public) for comparative analysis. Thus, focusing on communication and storage, adjusting the users' energy consumption behaviour in parallel with relevant technological interventions.

End user services provide a range of web-based utilities which may be used by a variety of user interfaces and other external systems. This component operates with the *Building Knowledge Base* to extract data about specific buildings and collections of buildings, to supply the customer with building data and comparisons. It uses the semantic processing services of the *Representation and Reasoning Tier* to provide the adaptive, context-sensitive elements of the end user services. Similarly, it uses services implemented by the *Data Capture Engine* to provide real-time elements of the end user services.

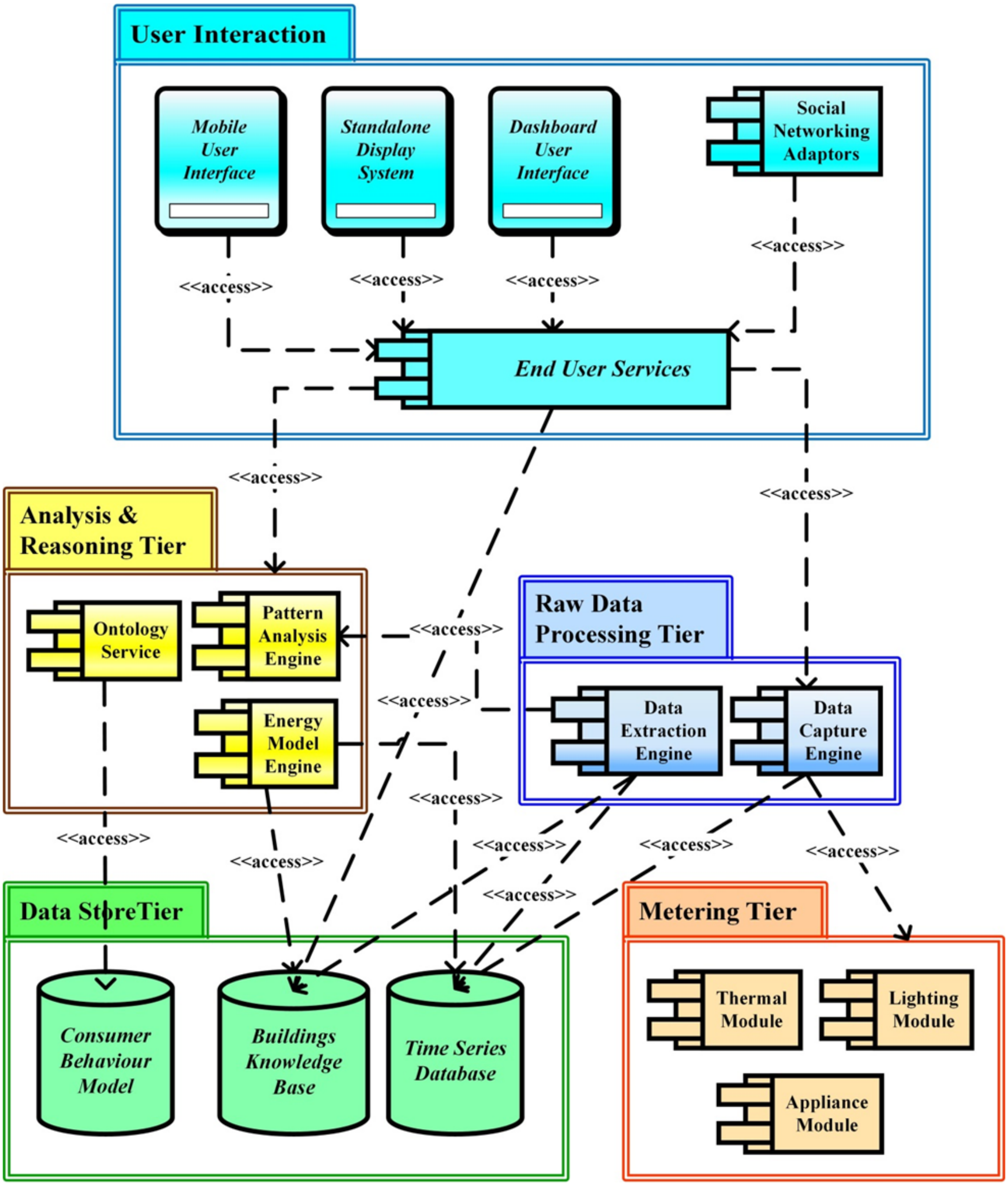

Figure 2. Generic architecture of energy management system

This is based on raw data and the *User Database* utilities to carry out authentication and authorization, to present the customer with the extracted user data. *Social networking adaptors* implement architecture to support the building of adaptors and to allow the integration of power consumption monitoring system into a range of separate social networking services.

The *Analysis and Reasoning Tier* provides a range of intelligent, adaptive services to be used mainly by the *End User Services*. It extracts parametric data on specific buildings and groups of buildings from the *Building Knowledge Base* to support its reasoning, and likewise uses the services of the *Ontology Service* as required. It also sends requests to the *Energy Modelling Engine* for predictions in relation to specific buildings. The *Ontology Service* provides generic ontology services to support reasoning, based on a purpose-built ontology for household energy usage and related data. This service allows users to make queries about energy consumption and other similar information. The tools can analyse the requests and collect the relevant data to generate an appropriate response.

The proper implementation of these tools is a semantic online analytical processing (OLAP) which consists of semantic web technologies and intelligent mechanisms that alleviate schema inconsistency. Thus, improving the cube capability for semantic interpretation and reusing the existing cubes, building new composite cubes to meet new requests. The users may pose different information requests to the system, but some requests are repeated directly or indirectly in the queries. Ontology in the semantic OLAP can in general be divided to domain ontology and OLAP cube ontology.

The domain ontology, for example, includes a building appliance ontology which contains the taxonomy of building appliances and their associated attributes; an energy ontology which includes energy measurement and properties; an environment ontology which defines position coordinates, distance, height, and other characteristics; and an action ontology which has a number of control actions for an actuator that it may take. The schemas of the data collected from different sensors, which are stored in the data warehouses, are mapped to the terms defined in these ontologies. Rules, procedural functions and ontologies can be used to model the necessary steps and inferences, thus acting as a bridge for the gaps and conducting attribute mapping and transformation. The ontology can be also used to model different data schemas provided by data sources, as well as, to ensure that the names and semantics of these schemas are consistent in the data cube.

The *Energy Model Engine* provides energy usage predictions based on built-in parametric models of generic building energy properties and on specific parametric data characterizing each building. It extracts specific parametric data on buildings and groups of buildings to support predictive modelling.

The *Pattern Analysis Engine* provides a range of generic pattern analysis algorithms to support extraction from the time series database. It is capable of classifying power consumption patterns using current data collector history for that particular device. The *Pattern Analysis Engine* needs to be able to analyse, classify and store additional consistent data related to the power consumption signature. This data (total power consumed during the event, number of times the pattern has occurred, duration of the event) is stored in the central repository's energy pattern storage database. Later, the reasoning engine will use this information to classify the pattern of energy usage and offer intelligent suggestions to the customer. This is based on elements such as the most frequently used energy consumption pattern for a known device, the total power used by a certain device within a given period, the patterns with the lowest energy used. User intervention will be required at different steps in the suggestion process, as the reasoning engine sees fit, in order to determine more accurately which habits are best for reducing power consumption.

The *Data Extraction Engine* carries out continuous or periodic analysis of the raw time series data to provide summarized and parameterized data for use in reasoning and prediction, according to abstractions that are defined in the schema of the *Buildings Knowledge Base*. It uses a query interface provided by the *Time Series Database* to extract raw time series data for analysis. Likewise, it makes use of the generic data processing and pattern analysis utilities of the *Pattern Analysis Engine*, as well as, uses operations maintained by the *Buildings Knowledge Base* to insert new entries related to specific buildings.

The *Data Capture Engine* is the server system that receives and processes raw time series data from the data capture systems in each of the buildings. It packages data appropriately to be collected in the time series database and provides suitable cached data to support the real-time elements of the end user services.

Several virtual control nodes are established on the *Metering Tier* (which communicates with the *Data Capture Engine*). They are configured as modules that address the following specific energy areas:

- The *Thermal Module* incorporates the sensors and actuators that are located throughout the building as part of the HVAC (heating, ventilation, and air conditioning) system.
- The *Lighting Module* incorporates the sensors positioned to monitor the use of lighting across the building. These sensors are deployed across the dwellings and detect inhabitancy and light. Remote actuation is put in place to enable the building manager to control the lights in response to occupancy and light sensor data. Sensors are positioned around work zones to measure direct and surrounding lighting. The data is used to develop ambient light profiles for different times in the day, which can be implemented through remote actuation in response to sensor feedback on lighting levels.
- *The Appliance Module* enables configuration and control of plug-level sensors placed across appliances and services in the building. Those smart devices are connected via wired or wireless communications, allowing the user to monitor the building remotely, change settings on an appliance, and control building tasks through a laptop or mobile device.

Extensive use of sensors for thermal, lighting, and appliance energy use will deliver granular measurement, establishing a prospective business case for sensor deployment. These cases demonstrate the level of savings enabled through more accurate measurement, balanced against the costs of deployment and operation. Exploiting the power of IoT brings the possibility of enhancing power consumption and well-being by building Energy Management Systems. The potential of the IoT lies in capturing new data, analysing it, and acting on it in an automated fashion.

The *Buildings Knowledge Base* stores parametric data on buildings monitored by the system, and provides query services to extract data about specific buildings and summary data about groups of buildings, selected according to criteria set out in predefined profiles. The purpose of the knowledge base is to form an integrated repository of sensor data using the energy behaviour of the buildings. This includes historic data, and covers:

- aggregate energy usage, i.e. absolute energy consumed in the building;
- functional energy usage, i.e. the power usage of different business functions in the building (e.g. office, kitchen, server room, etc.);
- sub-system energy usage (e.g. lightning, HVAC);
- granular energy usage, i.e. power used by individual appliances;
- thermal performance of the building.

The technology to enable this is a column-oriented NoSQL database management system. The innovation covers power consumption data in its breadth and depth. It will generate the most detailed longitudinal view to date of buildings' energy enhancement.

The *Time Series Database* stores the raw time series data collected from each of the buildings. In addition to the ability to store data streamed through the data capture engine, it provides query services to allow data to be retrieved for analysis, primarily by the data extraction engine. The development of an Energy Management System lays on smart metering energy performance models, which analzes the way of consumption as well as the level of power usage. To achieve these performance models, energy monitoring brings together sensor data from critical areas, such as appliance performance. As sensor readings are expected to occur from various sources, it is expected that the generated data collection is essentially a very large database that supports storing and generating statistical measures on sensor data. Sensor reading data comes from various sources: energy meter systems and supporting sensors or directly from appliances and services in the building. This data has to be stored and analysed against business intelligence to provide statistical and practical information to the managers, therefore to be accessible by using different means of communication. The petabyte data needed for collection will be delivered from sensors which belong to the Internet of Things. In an Energy Management System, the implementation of a distributed data warehouse would be better based on a column-oriented NoSQL DBMS. We offer the use of Hypertable DBMS as a real data warehouse implementation. This decision was based on the requirements of the data model, the types of requests, the amount of data to be stored and the benchmarking results [7], [29]. Hypertable DBMS offers the largest number of insert operations per second (on average) and a reasonable rate of scan operations. Considering that scan operations are supposed to be performed at a lower rate than insert operations, Hypertable exhibits good performance. Indeed, it could be considered as an option for the distributed data warehouse implementation in the architecture of the Energy Management System's. The Hypertable data model is column-oriented, consisting of a multi-dimensional table of information that can be queried using a single primary key. Hypertable (see http://hypertable.com) is high performance, scalable DBMS, which is open source and is modelled after Google's BigTable [21], [28], [36], [42]. Resilient to machine and component failures, the Hypertable manages and processes huge chunk of information stored on commodity servers. The data in the table is stored by primary key and is not typed into cells, but rather is stored as un-interpreted byte strings like in BigTable [8]. To obtain scaling, the table is broken into adjacent fields and is partitioned between various devices.

The *Consumer Behaviour Model* has a significant impact on deciding the user's power usage behaviour that is critical to achieving decrease in the energy demand. Understanding and controlling how people make choices on the energy they consume, whether consciously or unconsciously, is essential for achieving energy efficiency. This crucially depends on users' interpretation of the provided information and the way they response. People must be encouraged to use any chance which can benefit their wise consummation of energy.

5. Conclusion

This paper presents an Energy Management System architecture which allows heterogeneous, distributed querying and encompasses semantic enrichment and the personalisation of query processing mechanisms. In terms of consumption, information and energy-saving awareness among end users, the proposed system lets end users review their consumption in detail. This encourages users to change their behaviour, therefore reducing energy costs. Through the different interfaces shown in Figure 2., end users are able to view all kinds of appliances, power consumption information and corresponding costs clearly and intuitively.

The Internet contains thousands of frequently updated, time stamped and structured data sources which are not being stored, parsed, aggregated or queried. New data management systems with new interfaces, parsers, storage engines and delivery mechanisms need to be developed to deal with this transient, yet rich and highly useful information. The IoT database research offers new opportunity and challenges. The IoT's necessary speed and required low latency for its many applications are beyond current capabilities. Furthermore, its demand architecture is beyond that of current database server clusters and distributed databases. The power of the IoT comes from capturing data that has not been captured in the past, analysing that data, and providing process control by which to act on that data. The idea's major priority is to find appropriate procedures for storing, indexing, accessing, and querying semi-structured data, as well as data streaming, sampling continuous data, and data mining.

Big data decisions facilitate the ability to rapidly analyse extremely large data sets, like those associated with smart meter technologies, which improve the generation and transmission of assets. This allows for improved analyses of historical trend information. The cost of developing and maintaining a large-scale data store via the use of readily available and economical 'commodity' equipment is also reduced.

The proposed Energy Management System architecture and database management system may be an attractive option for stakeholders, such as municipalities administering public infrastructure, who are considering new scenarios in their efforts to optimise their costs and benefits. Providing easily understandable information to the end-user can help clarifying the outcome of the smart meters' performance, which leads to the development of higher innovative decision support systems. Applying data analytics to the gathered metering data would allow the system to raise energy awareness by providing tailored energy feedback. Combined with actuation capabilities, stakeholders would be able to foresee this information and use it to automatically optimise energy consumption, thus increasing their buildings' energy efficiency.

In the face of ever-growing energy demands but finite resources, behaviour plays a huge role in energy efficient practices. Therefore, great effort is still needed to get all people (officials and private companies) on board and capture the vast potential of energy savings in every community, industry, workplace and household. In addition to the technological and structural changes, which together set the needed transformation processes into motion, human behaviour is the element that helps sustain all energy-saving efforts. It has been acknowledged that technical improvements carried out in isolation tend to have a lower impact on energy savings than those combined with measures intended to encourage behavioural change. This confirms the importance of our consumer behaviour model which takes under consideration the user's role in power usage as critical to the reduction of energy demand.

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