THE ROLE OF IOT DATA AGGREGATORS FOR OPTIMISING OBJECT TRACKING AND KPI MONITORING

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Abstract

The Internet of Things (IoT) is an innovative technology that has completely transformed how different devices communicate. This includes sensors, actuators, GPS trackers, and other intelligent equipment. Among its many applications, one of the most important is its role in object tracking and monitoring Key Performance indicators (KPI). These functions are particularly crucial for logistics, manufacturing, agriculture, and retail industries.

The main objective of this paper is to explore the significance of IoT data aggregators in optimising these business processes. IoT data aggregators have a vital role to play as they gather, process, and analyse data from multiple IoT devices. This comprehensive approach allows a thorough understanding of the monitored objects and their performance. Moreover, the paper investigates how software designed for data aggregation can enhance the accuracy and efficiency of object tracking. This improvement facilitates real-time tracking of objects indoors and outdoors, analysis of past movements and events, and even predictive maintenance.

Additionally, the paper examines how data aggregators contribute to improved KPI monitoring by providing real-time performance metrics. These metrics enable proactive decision-making and enhance operational efficiency. However, addressing some technical challenges associated with object monitoring and data aggregation is essential, such as interoperability and vendor-free technology.

Keywords: IoT data aggregators, object tracking, Key Performance Indicator, KPI monitoring, operational efficiency

1. INTRODUCTION

In today's academic realm, it becomes apparent that further investigation is necessary to delve into the significance of IoT data aggregators in optimising object tracking and Key Performance Indicator (KPI) monitoring processes. While existing studies explore the utilisation of IoT technology for these intentions, they overlook the pivotal role data aggregators play in collecting, processing, and analysing the vast amount of data generated by IoT devices (mainly sensors and actuators). The current research primarily centres around IoT devices and implementing data analytics techniques for object tracking. However, limited attention has been given to the importance of data aggregators in effectively managing data flow between IoT devices and analytics systems.

This paper seeks to explore the implications of using software designed specifically for data aggregation to strengthen the accuracy and effectiveness of object tracking. This advancement aims to provide the information required for business analytics and reporting. The data analysed can provide insights that can shape strategic business decisions. The field of the article is Information Technology and Economics, explicitly focusing on the Internet of Things (IoT) and Data Analytics.

The field and topic of this work are important because IoT and Data Analytics, along with the ever-present Artificial Intelligence, are key drivers of today's digital transformation. These areas are necessary for all economic industries.

Furthermore, IoT devices generate considerable data that can be analysed in real-time. That is particularly important in healthcare, manufacturing and logistics industries, where real-time data can save lives, prevent downtime and optimise supply chains. When the field of data analytics (Data Analytics) is added to this, which enables the prediction of future trends and behaviour, it allows a much simpler transition from a reactive practice to a proactive one. By analysing previous data and using different prediction algorithms (predictive algorithms), it is possible to change the way of doing business and making decisions significantly. Suppose we add the ability to monitor the company's performance by defining and tracking KPIs. In that case, it is possible to additionally automate routine tasks and have information about business processes practically instantly. There are infinite examples, and this paper focuses on a sample from the logistics field, i.e., the analysis of vehicle driving quality, which is impossible using classic GPS devices.

In conclusion, IoT industry monitoring, data analytics and the ability to monitor economic indicators are essential and crucial for the growth and sustainability of companies and economies in the 21st century. Digital transformation is currently based on technical platforms that are not mature and sufficiently interoperable. Not to mention that the challenges of ensuring data security in the IoT world are a broad and exciting topic of their own.

The research gap in this article is the technical challenges associated with object monitoring and data aggregation in the context of IoT. By reviewing the current literature, we can conclude that some of the main concerns and research gaps nowadays regarding this topic are the following:

- What scalable solutions can be developed to handle the increasing volume of data generated by IoT devices?
- What strategies can be developed to enable real-time analysis of the massive data generated by IoT devices?

- How can interoperability among IoT devices and platforms be improved to facilitate seamless data integration and analysis?
- How can businesses overcome the challenge of vendor lock-in in IoT solutions?
- What methods can be employed to improve the quality of data IoT devices collect?
- How can the security and privacy concerns associated with IoT be effectively addressed to prevent data breaches and privacy violations?

To sum up, the main question can be asked: which technology platforms for data aggregation will integrate all the necessary functionalities required for further digital transformation?

This paper provides an overview of more recent research on the mentioned topic and a sample from the field of outdoor object tracking.

2. METHODS

The primary objective of this paper is to showcase how a data aggregator can be utilised as a foundation for business reporting and monitoring organisational goals using key performance indicators (KPIs). Due to the paper's length, we will not delve into the method of making business decisions based on analysed and presented data, as it should be self-evident. Instead, we will explain the data collection, aggregation, and analysis process.

Firstly, we explored the advances in indoor and outdoor object tracking technologies, as well as provide a review of the most important literature in the field.

We used state-of-the-art GPS/Glonass/Galileo 4G tracker devices and 3-axis accelerometers in eight vehicles to achieve this purpose. These vehicles were tracked via satellite (GNSS) for a one-week duration. The collected data, amounting to approximately 25 Mb, was extensively analysed. This analysis led to the creation a highly analytical report for the management. To ensure the accuracy of the data, we utilised the new generation devices, with Wialon services (Gurtam) serving as the analysis tool. The core concept of this paper centres around demonstrating the potential of consolidating various types of data into a unified source, commonly referred to as "data aggregators". This accumulation of data allows for simplified representation and facilitates efficient analysis.

Furthermore, we mention the possibility of conducting further data analysis using artificial intelligence systems and Neural Language Processing. It offers the potential for gaining additional information if a need arises and better insight into what is of great value for making decisions. It also leads to a better understanding of business data and a better definition of Key Performance Indicators.

3. RESULTS

3.1 Literature Review

Numerous research papers discuss various aspects of GPS outdoor and indoor positioning and tracking, as well as technological aspects of data aggregation and its impact on business processes. Also, numerous papers discuss their usability in real-world scenarios. Some essential papers and their references are mentioned in this chapter, and some papers are in the following chapters of the research results.

Bakhru 2005 explores different outdoor and indoor tracking techniques, including GPS modifications for indoor applications and additional sensors like IMU and MEMS. Hutabarat (2016) combines RFID and GPS for human tracking in both indoor and outdoor areas, achieving high accuracy. Gerdisen (2014) focuses on GPS-based human tracking in closed areas, developing an Android application with an error estimation of around 4 meters, which is more than expected. These papers provide insights into using GPS for outdoor tracking, including vehicle and human tracking, and highlight the potential of combining GPS with other technologies for improved accuracy and coverage.

Numerous papers collectively provide insights into IoT data aggregators. Uddin (2017) proposes a dynamic clustering and data-gathering scheme for IoT in agriculture, utilising an Unmanned Aerial Vehicle (UAV) to assist ground IoT devices in forming clusters and establishing a reliable communication backbone. Saleem (2020) highlights the importance of data analytics in IoT applications, emphasising its role in extracting meaningful insights for intelligent decision-making and performance optimisation. Arora (2017) presents a multi-representation-based data processing architecture for IoT applications, storing data in multiple representations to cater to diverse application demands and enabling real-time analytics. Farrell (2022) in their work introduces the IoT2SD framework, which incorporates an Intrusion Detection System (IDS) to structure unstructured IoT MQTT message data for data analytics purposes. This paper also covers the importance of data security in the IoT world. In addition to others, these papers discuss various approaches and frameworks for aggregating and processing IoT data. They highlight the benefits of efficient data analytics and the potential applications in different domains and industries.

When we seek to provide insights into key performance indicators for the Internet of Things (IoT), there are numerous papers in this domain as well. Malier (2016) emphasises the importance of digital technologies, such as FD-SOI, in enabling IoT devices to combine edge computing capabilities with RF or sensor functionalities. Lai-wu (2011) discusses key technologies based on RFID for achieving intellectual identification, location tracking, and management in IoT applications. Babu (2017) focuses on the performance analysis of data protocols in the network tier of IoT, reviewing protocols like MQTT, MQTT-SN, AMQP, CoAP, XMPP, and DDS and comparing them based on metrics such as network packet loss rate, message size, bandwidth consumption, and latency. Also, numerous papers point out how to prepare IoT-based Big Data for analysis (Kumar et al., 2022). In summary, these papers collectively highlight the significance of digital technologies, RFID-based technologies, and data protocols in ensuring the efficient performance of IoT systems with a straightforward key point in mind - how to create a solid standpoint to measure their performance.

3.2 Current Advances in Object Tracking Technologies

In today's increasingly connected world, the ability to track objects has become a crucial aspect of our daily lives. Whether monitoring the movement of goods in a warehouse or keeping track of personal belongings, indoor and outdoor tracking systems have revolutionised how businesses manage and locate objects. This report explores the nuances of indoor and outdoor tracking, shedding light on the various technologies and methods involved. Vital factors contributing to the successful and confident tracking of objects are understanding the differences between indoor and outdoor environments, harnessing the power of GPS and geostationary satellite systems, leveraging Bluetooth, UWB and IoT technologies, and utilising data aggregators. By delving into the intricacies of these factors, we can gain a comprehensive understanding of the advancements in object tracking and their implications for various industries.

3.2.1 Advances in Outdoor Object Positioning

Global Navigation Satellite System (GNSS) is the central outdoor object positioning and tracking technology. The system is formed from geostationary satellites and required receivers. Most new satellite monitoring devices (GNSS trackers) can simultaneously use more than one geostationary system. This allows location interpolation, leading to slightly more accurate results than relying only on one system. Geopositioning accuracy can vary between 2 to 10 meters, even in such cases. This variation is dependent on the location and various additional factors. Real-time Kinematic Positioning (RTK) corrections have shown the potential to achieve accuracy within a few centimetres (Kumar et al., 2021). However, that technology does not apply to devices in motion, and it is limited to stationary devices used for position collection (such as GMSS devices used for this research).

The issue of precise positioning is widely recognised and extensively discussed in a series of research articles. Numerous problems that are associated with geopositioning are primarily problems of a physical and technical nature. These problems encompass satellite and receiver clock errors, multipath errors, ionospheric delay, tropospheric delay, and GPS ephemeris errors (Kumar et al., 2021). Research on the possible use of a GPS receiver as an acceleration sensor has been conducted by, for example, Sokolova, Borio, Forssell, & Lachapelle (2010). The results seem to confirm that the mathematical model for that is satisfactory.

When it comes to outdoor tracking, the challenges become more complex due to factors such as (1) varying lighting conditions, (2) occlusions, and (3) unpredictable object motion. To overcome that, researchers have explored technologies such as Inertial Measurement Units (IMUs) and sensor fusion techniques. GPS and other satellite GNSS systems provide accurate location information by utilising signals from satellites, but its accuracy can be compromised in urban environments with tall buildings and signal obstructions. IMUs, on the other hand, use sensors such as accelerometers and gyroscopes to measure the object's motion and orientation. Combining data from multiple sensors using sensor fusion techniques can improve the accuracy and robustness of outdoor tracking systems (Huang et al., 2010).

Information regarding the acceleration of the monitored object cannot be solely derived from the current position data, as stated before. To attain this information, GPS tracker devices need accelerometers, which measure the G-forces acting upon the object along the X, Y, and Z axes. Incorporating a triaxial acceleration sensor and gyroscope enables the creation of comprehensive reports on eco-driving in automobiles or trucks. That includes not just the velocity attained from the satellite system but also measurements of the driver's level of aggression in acceleration, braking, and changing direction throughout the journey. A detailed analysis of a particular driver's behaviour becomes achievable by considering the anticipated G-forces for a typical passenger vehicle (which surpasses those observed in trucks or buses). This methodology significantly decreases fuel consumption and minimises the wear and tear on various vehicle components such as tires, suspensions, etc. The primary aim of all these efforts revolves around optimising fleet management costs. The application of IMU technology is viable in almost every aspect of object monitoring, irrespective of whether the object is indoors or outdoors.

If the precise location is not required for outdoor tracking, the unit does not need a GPS module at all. It can acquire its approximate position based on LBS data (Location-Based Services, Cell-ID) and information on what GSM repeater unit is currently connected. LBS location can be informative when there is no GNSS signal, devices must operate in low battery mode, or when the tracked object is inside a building where a GPS signal cannot pass through. LBS position is more accurate in the urban and more populated areas because there are more GSM repeaters. However, it can still show a false distance of about a few hundred meters and even ten kilometres in unpopulated areas (Samama, 2019).

Contrary to the widely held belief that GNSS technology has already peaked, it is undeniably constantly advancing and undergoing remarkable enhancements. According to Rizos (2005), significant improvements are anticipated from various perspectives soon from the (1) communication point of view, (2) instrumentation and techniques, (3) hardware and (4) software point of view. Those enhancements will additionally advance current technology for outdoor tracking.

3.2.2 Advances in Indoor Object Positioning

The precise tracking of an object's location within enclosed spaces such as buildings, underground parking lots, and airports is not feasible with GNSS technology. Multiple reasons exist for this limitation, including a significant decrease in signal quality and quantity from geostationary satellites within enclosed spaces. Additionally, various materials obstruct or reflect microwave signals, negatively impacting accuracy. Interferences also occur within the 1100 to 1600 MHz radiation spectrum, the range most GNSS receivers operate.

The GNSS positioning system offers a notable advantage because users do not need to invest in supplementary equipment installed locally. The sole requirement is possessing a GNSS receiver (tracker device). However, when it comes to indoor object positioning, aside from deploying a transmitter on the targeted object, one must also establish an infrastructure that facilitates tracking within enclosed spaces. That entails incurring extra costs and maintaining equipment such as WiFi hotspots, RFID antenna systems, BLE or UWB receivers, etc.

As a result of these factors, the indoor positioning system (IPS) relies on distinct technological aspects compared to GNSS. Primarily used for business purposes, IPS is widely adopted for navigation in commercial, military, and civilian domains. Retail is one field where IPS finds applications, allowing tracking customers within a store and enhancing understanding of their behaviour. Leveraging data on customer movement can lead to improved product placement, optimised store layouts, and personalised marketing messages. IPS facilitates tracking medical equipment and patients within a hospital setting. That helps enhance efficiency in areas like transportation and medication distribution. IPS can be utilised in an industrial environment for inventory management, monitoring resource mobility, and optimising manufacturing processes. It also contributes to reducing losses and enhancing worker safety while facilitating the implementation of the e-kanban, a digital version of the traditional kanban system used in lean manufacturing.

Wireless Bluetooth Low Energy (BLE) is an emerging IPS technology and the Ultra Wideband (UWB) technology. The precision and reliability of UWB technology have contributed to its increasing popularity, and it is expected to revolutionise indoor object positioning and tracking, offering precise positioning accuracy within about ten centimetres (Samama, 2019). That makes it ideal for indoor object-tracking applications that require meter-level accuracy, such as asset tracking, inventory management, and indoor navigation systems.

An essential factor to be considered pertains to the utilisation of data aggregators, which allow for the merging and processing of outdoor and indoor object-tracking data into a comprehensive and valuable source of information by incorporating location data with supplementary particulars like object specifications, accountable individuals, expiration dates, acceptable impact forces during handling, permissible temperature ranges, and other related data, a remarkably versatile system can be devised (Wang et al., 2022). This system not only tracks the locations of objects but also facilitates the efficient management of business operations.

3.3 The Usage of IOT Data Aggregators

The task of collecting, organising, and analysing data received from various IoT devices, sensors and actuators is managed by IoT data aggregators. These platforms or systems play a central role in this process. The devices that fall within the realm of IoT range from intelligent appliances and wearable devices to industrial machinery and environmental sensors. The capacity of IoT data aggregators lies in their ability to acquire data from diverse devices, regardless of their type or manufacturer, and consolidate it into a centralised location. This consolidation simplifies the management and analysis of the data. Aggregators can gather information from multiple sources, integrate it, and provide a unified perspective of the gathered intelligence.

Apart from consolidating data, these platforms often provide data cleansing, normalisation, and enrichment tools similar to ETL (Extract, Transform and Load) tools in Business Intelligence applications. These tools ensure the data's accuracy, consistency, and usability for analysis purposes. Many applications can "clean" the data and transform it into a format suitable for analysis (Lindel, 2020). Furthermore, IoT data aggregators may also offer storage capabilities for organisations to accumulate vast amounts of IoT data for future utilisation.

According to a study by Trappey et al. (2017), IoT data aggregators enable the integration of diverse data from various sources, including sensors, actuators, and smart devices. This integration occurs in a unified and standardised format, simplifying extracting meaningful insights and deriving effective intelligence (Trappey et al., 2017). By collecting and organising data from a variety of IoT devices, aggregators enhance the visibility and accessibility of data, thereby enabling more efficient data analysis. IoT data aggregators often incorporate advanced analytic techniques like machine learning and artificial intelligence to identify patterns, trends, and anomalies within the collected data. That enables real-time decision-making and predictive analytics. This capability proves particularly valuable in domains that rely heavily on timely and accurate data analysis. Therefore, IoT data aggregators serve as critical components within the IoT ecosystem, facilitating the extraction of insights from the massive volumes of data generated by interconnected devices.

It is worth noting that specific academic works even acknowledge that data aggregators can exist in hardware units, such as routers, access points, gateway devices, various stationary devices and even drones (Sharma et al., 2022). Notably, drones possess the unique ability to surveil inaccessible or hazardous locales, enabling them to gather information from sensors incapable of transmitting data across substantial distances due to their inherent technological limitations (e.g., WiFi, Bluetooth, RFID, and the like).

For an IoT network to be considered robust, it needs to possess the capability of handling malfunctions without compromising its connectivity. Reliable networks are necessary because they establish a dependable foundation for inter-device communication. IoT systems' nodes, or vertices (Dagdeviren et al., 2022), are typically interconnected through wireless channels and engage in message exchange. Consequently, when relay nodes encounter failures, data transmission between nodes can be disrupted, resulting in the inefficient utilisation of various resources. Thus, the underlying communication infrastructure of a reliable IoT network should be equipped with the ability to withstand failures and ensure the connectivity of active nodes.

There is a multitude of challenges that must be taken into account when we are speaking of network communication among IoT devices. One particular issue that stands out prominently is the need for interoperability among diverse devices. This limitation is often acknowledged as a crucial obstacle that needs to be addressed to establish a network that is both seamless and free from vendor restrictions (Rathanasalam et al., 2020), as well as a need for communication protocols in connecting devices and applications. These protocols enable smooth data exchange, establish device address schemes, and determine packet routing strategies (Mahbub, 2022). They also include functions like sequence control and flow control for optimal communication. Within the IoT realm, unidirectional and bidirectional communication among various devices must be logged in the database of a data aggregator. That enables the consolidation of all the data in one central location, thereby facilitating the preparation of reports using business intelligence analytical tools.

Since the data arrives in real-time to the aggregator, tracking Key Performance Indicators (KPIs) even daily is possible. KPIs can be identified and established at different levels, including daily benchmarks, and are commonly utilised to monitor and evaluate the accomplishments of organisational goals or projects. They can be established long-term to assess overall performance and track daily or weekly outcomes and progress at shorter-term levels. With enough computing power, stored data, and a good selection of long-term, middle term and short-term KPIs, we expect management to have a pretty good view of how business processes are conducted in almost real-time.

3.4 Exploring the Potential of Data Aggregators in Outdoor Object Positioning and Driving Quality Analysis

For this paper, we will analyse the data on outdoor object positioning. The situation with indoor object positioning of objects is similar, with certain limitations. Indoor tracking analysis, which relies on data from accelerometers (before mentioned IMUs), can provide valuable information about how goods are manipulated inside the warehouse. That data can be of high value if the business entity deals with sensitive goods. Likewise, additional information (besides g-forces) is obtainable from other types of sensors such as temperature and humidity sensors (if it is a heat and moisture-sensitive goods such as food), magnetic and PIR sensors, identification beacon sensors and the like.

For this paper, data from GNSS satellite tracking of eight vehicles equipped with Teltonika 4G FMC230 GPS/Glonass/Galileo devices will be analysed for outdoor object tracking. These devices are provided with additional 3-axis accelerometers that transmit location and acceleration data in real-time. The accuracy of location is achieved through simultaneous interpolation of 10-19 satellites. All the data is then aggregated in the Fleet Management System (FMS) Wialon, developed by Gurtam. Based on predefined rules, the system determines the driving quality for each vehicle individually. The resulting report assigns a driving quality score on a scale of 1-10, where a higher grade indicates driving that adheres more closely to safety regulations, speed limits, and G-force related to acceleration, braking, and turning. Violations related to speeding are penalised based on the specific road limits applicable to the vehicle's route. For each car, expected g-force values are defined, and penalties for exceeding the expected ranges are also established based on the vehicle type.

Acceleration calculations involve several data points, including:

- the unit's location,
- initial and final speed values,
- travel time between two points,
- the unit's movement direction, and

- particular parameters received from the device (G-forces).

Table 1 presents the chosen tangible values used to calculate and report the quality of driver behaviour.

Table 1 Acceleration values for driving quality assessment

Name	Criterion	Min. value	Max. value	Penalty
Acceleration: extreme	Acceleration	0.4g		2000
Acceleration: medium	Acceleration	0.31g	0.4g	1000
Brake: extreme	Braking	0.35g		2000
Brake: medium	Braking	0.31g	0.35g	1000
Harsh driving	Reckless driving	0.3g		300
Speeding: extreme	Speeding	41 km/h		5000
Speeding: medium	Speeding	21 km/h	21 km/h	2000
Speeding: mild	Speeding	10 km/h	21 km/h	100
Turn: extreme	Turn	0.4g		1000
Turn: medium	Turn	0.31g	0.4g	500

Source: own research

This table shows the criteria and acceleration values used to assess driving quality. The criteria include acceleration, braking, reckless driving, speeding, and turning. Each measure has a range of values representing thresholds for specific driving behaviours. Penalties are assigned based on behaviour severity, with higher penalties for extreme behaviours. For example, extreme acceleration (>0.4g) and extreme braking (>0.35g) receive a penalty of 2000. Medium acceleration and braking (0.31g-0.4g for acceleration, 0.31g-0.35g for braking) receive a penalty of 1000.

Reckless driving (acceleration >0.3g) receives a penalty of 300. Speeding is categorised as extreme, medium, and mild. Extreme speeding (>41 km/h) receives the highest penalty of 5000, while medium speeding (21 km/h) and mild speeding (10 km/h-21 km/h) receive penalties of 2000 and 100, respectively. Extreme and medium turning behaviours are also penalised. Extreme turning (acceleration >0.4g) receives a penalty of 1000. Medium turning (0.31g-0.4g) gets a penalty of 500.

In summary, this table provides an overview of how driving behaviours are assessed and penalised based on severity and impact on driving quality. The aim is to discourage dangerous driving and promote safe and responsible behaviour.

Analysis was executed using data gathered from one week-long drive, thereby revealing a comprehensive ranking of the driving quality of the eight vehicles mentioned above. Through an examination of this data, valuable insights regarding the driving quality of these individual vehicles are revealed, thereby facilitating well-informed business decisions concerning vehicle servicing requirements, as well as the potential for supplementary driver incentives for those who attain higher ranks or, conversely, measures to driver penalty if it is necessary. By correlating this ranking with the fuel consumption (assuming that all vehicles are exact type, model, and engine power), one can present valuable information regarding the potential for minimising overall business expenses for each vehicle. This report cannot be attained solely through GNSS tracker data but can be critical to business owners.

The results of the analysis and the final report are presented in Figure 1.

Figure 1 Driving quality assessment report

Unit	Rank	Penalty	Violations	Duration	Mileage, km	Trips
(693 IJ)	8.3	31	12	05:24:38	403.8	6
SAMIR (960 IF)	6.2	97	59	15:39:15	1249.9	14
DAVOR (165 IF)	5.4	140	100	13:52:23	1133.3	10
TOMO (470 HM)	4.9	172	109	16:55:50	1321.7	12
VRABEC (114 IH)	3.6	335	93	15:08:04	1204.0	12
PAVO (119 II)	3.5	356	97	14:01:39	999.6	14
KOVA (508 IK)	3.0	458	113	15:22:51	1376.6	13
SAMIR (420 HR)	2.9	496	258	18:04:08	1317.6	9

Source: own research

The analysis findings concerning driver behaviour and driving quality are presented clearly, utilising a table for easy comprehension. Each GNSS device and its corresponding g-sensors transmitted an average of 7,000 to 9,000 telemetry messages to the system. A total data accumulation of approximately 2 megabytes occurred, with approximately 1.3 megabytes transmitted and 0.7 megabytes received. These values indicate that nearly 35% of the data traffic is communication overhead, encompassing TCP/IP handshaking and maintaining an open TCP/IP connection. Considering the information above, it becomes evident that this reporting process has significant challenges from the CPU processing power necessary to handle this volume of data and the mentioned calculations.

4. THE IMPACT OF DATA ANALYSIS ON KEY PERFORMANCE INDICATORS

In today's digital age, data has become the lifeblood of organisations, fuelling growth and driving strategic decision-making. With the exponential growth of data, Big Data has emerged, revolutionising how businesses operate, compete and measure their KPIs. Integrating Big Data with Key Performance Indicators (KPIs) has opened up new avenues for organisations to measure and enhance their success. KPIs are not a new concept to companies (Parmenter, 20015), and they "represent a set of measures focusing on those aspects of organisational performance that are the most critical for the current and future success of the organisation". By examining the integration of accounting and economic indicators and the analysis of IoT data as a foundation for

KPIs, leveraging Big Data can facilitate informed decision-making and drive key performance measurements in various industries.

In 1992, Kaplan and Norton introduced the concept of balancing performance indicators and developed the Balanced Scorecard methodology, which translates business objectives into indicators across different dimensions. This has led to various operational approaches (Franceschini et al., 2019):

- the Balanced Scorecard method;
- the Critical Few method;
- the Performance Dashboards, and
- the EFQM (European Foundation for Quality Management) model,

Within data analytics, those models can easily be presented with a graphic user interface that shows the up-to-the-minute state of KPIs.

Big Data has emerged as a crucial tool for measuring and evaluating success in various domains since it refers to the vast amount of information generated from multiple sources. Such sources are web, emails and digital communications, social media, sensory data, and transaction records, and they provide opportunities for organisations to gain insights and make data-driven decisions. According to Wagner-Pacifici, Mohr, and Breiger (2015), Big Data analytics enables the identification and analysis of KPIs that can help assess an organisation's success. By harnessing large datasets, organisations can identify patterns, trends, and correlations that were previously unattainable with traditional data analysis methods. These KPIs can range from customer satisfaction metrics to financial performance indicators, depending on the organisation's specific objectives.

Furthermore, Big Data analytics can also facilitate predictive modelling and forecasting, allowing organisations to anticipate future trends and make proactive decisions. Associated KPIs have inevitably become indispensable tools for measuring and evaluating success, providing organisations with valuable insights and opportunities for improvement (Wagner-Pacific et al. 2015).

As Mikalef, Krogstie, Pappas, and Pavlou (2020) also highlighted, Big Data analytics enables organisations to identify key performance indicators (KPIs) crucial for measuring their success. Organisations can identify patterns and correlations by analysing large volumes of data to help them define meaningful KPIs. Furthermore, Big Data analytics allows organisations to monitor and track these KPIs in real-time, providing timely insights and the ability to make data-driven decisions. This ability to leverage Big Data for KPI measurement, as stated by authors, has been shown to impact organisational performance positively and can lead to increased competitiveness and profitability.

According to a study by Gandomi and Haider (2015), Big Data analytics allows companies to identify key performance indicators (KPIs) crucial in evaluating their success. By "harnessing the power of big data", businesses can measure sales, customer satisfaction, and operational efficiency metrics to assess their performance and make data-driven decisions. The study emphasises that big data analytics provides organisations with real-time and accurate information, enabling them to monitor their KPIs effectively and make timely adjustments to their strategies. Therefore, big data plays a pivotal role in helping businesses identify and evaluate key performance indicators, leading to improved decision-making processes and overall success in today's data-driven world.

As Wagner-Pacifici, Mohr, and Breiger (2015) also pointed out, big data provides organisations with much information that can be used to gain insight into the company's operations and to make the so-called informed decisions. With the proliferation of digital technologies and the Internet, vast amounts of data are generated and collected daily. As the researchers conclude (Lindell, 2015), with the emergence of digital technologies and the Internet, large data sets have become vital in measuring KPIs and enabling data-based decision-making and business optimisation. The analysis of Big Data is significantly impacted by Neural Language Processing (NLP), which can also be used in this scenario. There are several ways in which NLP can enhance the analysis of extensive datasets (Sharma et al., 2022).

In the previous text, sources are presented that point to a long-known fact: for business analysis, it is necessary to have good data sources and reliable metrics and methodologies by which these data are analysed and presented. This paper presents an example of data analysis within the logistic process of vehicle monitoring and the combination of indoor and outdoor object positioning. The possibilities arising from data aggregation (merging) led to introducing a concept known as Intelligent Logistics System Based on IoT (Wang et al., 2022).

5. DISCUSSION AND FUTURE CONSIDERATIONS

This paper aims to help understand the vital role played by IoT data aggregators in transforming business processes, particularly in sectors where an object positioning system (indoor and outdoor) is a must, like logistics and manufacturing, retail and even agriculture. The findings indicate that these data aggregators play a significant role in enhancing the possibility of object tracking by collecting, processing, and analysing data from IoT devices. That enables real-time tracking and more than just analysis of past movements. Furthermore, it demonstrated that the contribution of data aggregators extends to improving KPI monitoring by providing real-time performance metrics. That facilitates proactive decision-making, operational efficiency and predictive maintenance.

There are numerous possible implementations in practice. Some specifics would be energy management (this can lead to significant cost savings and a reduced environmental impact), Agriculture (increased crop yields and reduced costs), Environmental Monitoring (improved environmental conservation efforts) and so on.

Despite the numerous benefits, it is crucial to address technical challenges associated with data aggregation, such as interoperability and vendor-free technology. Integrating Big Data with Key Performance Indicators (KPIs) significantly impacts how organisations measure their success. The abundance of information from diverse sources empowers organisations to gain valuable insights and make informed decisions based on data. By leveraging Big Data analytics, organisations can uncover previously undiscovered patterns, trends, and correlations, facilitating the identification and analysis of KPIs. These indicators encompass a wide range of metrics, covering aspects from customer satisfaction to financial performance, providing organisations with a comprehensive understanding of their business.

Big Data analytics enables predictive modelling and forecasting. That analytics empower organisations to anticipate future trends and make proactive decisions.

Despite the numerous benefits offered by IoT data aggregators, several technical challenges need to be addressed, including data security and privacy, interoperability and cost-effectiveness. Future research should focus on solutions that fully enable the potential of IoT data aggregators as database storage for future analysis while considering the associated challenges. That may be done with numerous systems like Apache Pulsar, NATs, RabbitMQ, Apache Flink, Samza, Redis Streams, Apache NiFi, Flume and, for example, RocketMQ. Many of these systems/platforms integrate required data aggregation possibilities, but more research should focus on standardising needed functions. One of the open questions is whether open-source distributed data streaming platforms like Apache Kafka can provide all the required functions. It is designed for high-throughput, fault-tolerant, and scalable data streaming, allowing large volumes of data to be processed and aggregated in real-time. Also, it can collect, store, and process data from various sources, making it suitable for use as a data aggregator in big data and real-time analytics applications.

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