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Augmenting context with power information for green context-awareness in smart environments

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The increase in the use of smart devices has led to the realization of the Internet of Everything (IoE). The heart of an IoE environment is a Context-Aware System that facilitates service discovery, delivery, and adaptation based on context classification. The context has been defined in a domain-dependent way, traditionally. The classical models of context have been focused on rich context and lack Cost of Context (CoC) that can be used for decision support. The authors present a philosophy-inspired mathematical model of context that includes confidence in activity classification of context, the actions performed, and the power information. Since a single recurring activity can lead to distinct actions performed at different times, it is better to record the actions. The power information includes the power consumed in the complete context processing and is a quality attribute of the context. Power consumption is a useful metric as CoC and is suitable for power-constrained context awareness. To demonstrate the effectiveness of the proposed work, example contexts are described, and the context model is presented mathematically in this study. The context is aggregated with power information, and actions and confidence on the classification outcome lead to the concept of situational context. The results show that the context gathered through sensor data and deduced through remote services can be made more rich with CoC parameters.

KEYWORDS

context, contextual data, cost of context, power information, IoE

1 Introduction

The turn of the millennium has observed many advances in science and technology. Ideas have been refined and realized to improve human life. Among these ideas, the concept of a world is connected through seamless smart devices, which access remote services. This idea came to the mind of Mark Weiser and termed pervasive computing, where the computing would be dependent on ubiquitous and pervading devices or machines. Meanwhile, the advent of mobility and smart devices introduced mobile computing as an evolution of pervasive computing. The development of smart, inexpensive, and universally accessible devices led to the dawn of the fourth industrial revolution commonly known as Internet of things (IoT; World Economic Forum, 2021; Elgazzar et al., 2022). The increase in computing power of small devices has now evolved IoT to Internet of everything (IoE; Vaya and Hadpawat, 2019; da Costa et al., 2021). An IoE environment includes sensors, devices, appliances, and remote services that interact with each other. Such an environment is also termed a smart environment (Horng, 2023). Over the years, the devices have become compact, powerful, and communicate seamlessly

(Mahmud et al., 2007b; Hussain et al., 2020). The world is envisaged to be amalgamation of smart environments. It is expected that by the turn of this decade, there will be 75 Bn devices, generating 1TB data per environment daily. The data are generated by sensors and services. The 4th industrial revolution has enabled IoE environments (World Economic Forum, 2021). According to Statista (2020), there were 27 billion devices connected in 2019, and this will increase to 75 billion in 2025. IoT analytics estimated 12.3 billion connected devices in 2021 (Lueth, 2022). Cisco estimates the number of connected devices to be a trillion in 2025 (Cisco, 2016; AlliedTelesis, 2021). The International Data Corporation (IDC) predicts more than 40 billion devices that will generate 80 zettabytes in 2025 (Rizvi et al., 2020).

Within a smart environment, the data generated are used to facilitate smart service discovery, delivery, and adaptation (Schilit et al., 1994; Mahmud et al., 2020). This data include all information and can be used for activity recognition or context awareness (Abowd et al., 1999; Mahmud and Javed, 2012). The context is collected, transformed, stored, and then classified. The context is classified into activities using machine learning algorithms (Mahmud et al., 2007a; Mahmud and Javed, 2014; Mahmud, 2016). Recently, researchers have used deep learning to classify context (Bashir et al., 2023; Keramatfar et al., 2023). This is termed context inferencing or context processing (Mahmud et al., 2022b; Casillo et al., 2023). Once the context is classified, appropriate actions can be taken (Augusto et al., 2022). For example, the change in the orientation of a smartphone is based on the orientation of the user, or the change in the screen brightness is based on the ambiance. The context has been modeled as a set of attribute-value pairs. These can be represented as open web standards including XML, RDF, and OWL. Swenja et al. (2022) have used OWL to develop a context model that is composed of two sub-models. The Entity Model and the Instance Model are the sub-models of the context in the domain of smart manufacturing.

Many researchers have described the context since its inception in 2001 (Schilit and Theimer, 1994). The definitions have both philosophical and domain-based perspectives. The philosophical basis demands that the context include all information, whether relevant to the domain or not. The domain perspective views the context as a set of attribute-value pairs that help classify the context for activity recognition. This is the classical view of the context which refers to a set of attributes that better classify the context. Both these techniques are either too general or too specific. This hinders the sharing and reusability of contexts gathered in different domains. Furthermore, these perspectives lack a futuristic view of context. There is a need to redefine context with its core in philosophy and have the ability to be domain-independent. Zouhaier et al. (2013) have stressed the need for a rich context that can model the contextual information.

An IoE environment includes battery-operated devices that interact with each other. Power consumption is a constraint, and interactions should be energy-efficient (Li et al., 2015; Caiazza et al., 2024). While the context has been described by many researchers over the years, this study presents a model that includes power information as part of the context. The basis of including power information within the context is that power is a constraint in smart environments, in which the users interact with services via battery-operated environments (Mahmud et al., 2022a; Martyushev et al., 2023). The contemporary work in context definition lacks the power information. The philosophical basis of context demands that everything that can be used to describe the context can be included within the context. The concept of quality of context (QoC) and the cost of context (CoC) have been described in the literature. The contributions of this study are as follows:

- The authors present a formal mathematical definition of context that includes power information as a CoC which can be used in decision support within an IoE environment. This introduces power information as an addition to the traditional definition of context. The impact of power information, including energy consumption, is a constraint for battery-operated devices and must be included within the context to enable green context awareness.
- Finally, an example case is presented to show a snapshot of the context based on the proposed mathematical model of context. This serves as proof of concept for the proposed formal model of context.

The rest of the study is organized as follows: Section 2 presents the evidence in the literature. Section 3 describes the components of an IoE environment. Section 4 presents the mathematical model for green context awareness. Section 5 discusses a case study for proof of concept. The study concludes in Section 6.

2 Evidence in literature

The brain of a smart environment is a context-aware system. The system receives contextual information, analyzes it, and assigns it an activity label (Alegre et al., 2016; Hashemi and Sadeghi-Niaraki, 2016; Kirsch-Pinheiro, 2023). A context-aware system communicates with sensors and services in a smart environment and processes the context using machine-learning techniques (Ogbuabor et al., 2022). Various techniques have been presented in the literature to model context (Mahmud et al., 2007c). Kaenampornpan and O'Neill (2004) have used activity theory to model context. Engelenburg et al. (2019) have presented a mathematical model by using predicates to model context. Lupiana has used actor network theory (ANT) to model context as an interaction between human and non-human actors (Lupiana, 2017). However, this study focuses on the composition of the context rather than the modeling technique.

Schilit et al. (1994) and Schilit and Theimer (1994) presented the pioneering concept of context as all information covering a user, the user's environment, and the services or applications bound within the user's environment. This type of context could be represented as predicates that could be triggered based on the context. This context has a domain perspective and is used for the ParcTab application. The ParcTab is a location-aware application that diverts calls to the nearest phone, based on a user's location, and senses using RFID cards.

Brown (1995) presented a similar view where the context is a collection of information that a machine knows, which is bounded by the user's proximity. While this is a generalized perspective, the stick-e document, proposed by Brown, can be used to develop context-aware applications. The composition of

TABLE 1 Comparison of contemporary literature.

Related work	Rich context	QoC	CoC	Power information
Schilit et al. (1994)	✗	✗	✗	✗
Brown (1995)	✗	✗	✗	✗
Abowd et al. (1999)	✓	✗	✗	✗
Dey (2001)	✓	✗	✗	✗
Zhu et al. (2018)	✓	✗	✗	✗
Riaz et al. (2005)	✓	✗	✗	✗
Bazire and Brézillon (2005)	✓	✓	✗	✗
Sheng and Benatallah (2005) and Sheng et al. (2009)	✓	✓	✗	✗
Mahmud et al. (2007a,b)	✓	✓	✗	✗
Buchholz et al. (2003)	✓	✓	✗	✗
Manzoor et al. (2008)	✓	✓	✗	✗
Camargo-Henríquez and Silva (2022)	✓	✓	✗	✗
Klimek (2022)	✓	✓	✗	✗
Thi et al. (2022)	✓	✓	✗	✗
Jagarlamudi et al. (2021)	✓	✓	✓	✗
Kouamé et al. (2020)	✓	✓	✓	✗
Freitas et al. (2021)	✓	✓	✓	✗
This paper	✓	✓	✓	✓

the context is limited to include all information that is suitable for user–machine interaction.

Abowd et al. (1999) and Dey (2001) presented a philosophical perspective inspired by the ability of humans to use situational information as the context. The context now includes all the information that can define and characterize a situation or group context (Zhu et al., 2018). This concept is inspired by a philosophical perspective, and Dey has developed a context toolkit, which is used to develop context-aware applications. The context toolkit is bounded by considering the situation as an interaction between a user and an application or service.

Bazire and Brézillon (2005) have considered context as a set of constraints on the eventual behavior of a system. This means that the context derives from the service behavior. This perspective is based on the machine–user interaction. Sheng and Benatallah (2005) and Sheng et al. (2009) have also considered context as relevant information which is useful to adjust the execution and outcome of a service. Specifically, Sheng used Unified Modeling Language (UML) to represent and model context.

Riaz et al. (2005) described the context as the information describing users, services, and the context-aware application or middleware. This introduced a new dimension, where the context of the context-enabling middleware is included. However, Mahmud et al. (2007a,b) argued that if the context-enabling middleware is implemented as a context-aware service, keeping the context of the context-enabling service is redundant. It should be a part of the service context. These two authors considered context as a mechanism to facilitate service discovery and delivery based on the context. While both researchers have considered context to be rich in information, the information related to the action performed after the context is classified, which is not included in the context.

Klimek (2022) has developed a context data model and has considered police interventions as a case of context awareness. The author has considered context to be a collection of facts that describe a state. However, the context defined is rich and domain-oriented. Thi et al. (2022) propose a knowledge model for context that describes context using services, service systems, and a network of service systems and present a case study of context-aware chatbot services.

The context is a collection of attribute-value pairs of contextual information. Each context is unique, but multiple contexts can belong to the same situation. Buchholz et al. (2003) introduced the concept of quality with contextual information. Quality of context (QoC) is a quality attribute defining the quality of contextual information. For example, a context can have GPS data as contextual information. GPS data would generally include latitude, longitude, and altitude. Depending on the location, i.e., indoors, outdoors, or in remote areas, the quality of the GPS data would vary. Bucholz et al. present the quality of each contextual data to have multiple facets. These include precision; how close is the value to the actual value, granularity; the finesse of the value, freshness; how up-to-date the value and trust; how trustworthy the value is (Mahmud, 2012; Mahmud et al., 2012).

Buchholz et al. also parameterized QoC using probability of correctness which gives the correctness of contextual information as a probability. While the probability of correctness and precision have different values, they both refer to the same concept and are redundant. A normalized value of precision would serve just as the probability of correctness. Manzoor et al. (2008) enhanced the QoC parameters to include completeness; how complete a multi-valued attribute is, and significance; the worth of the contextual information, similar to precision.

Recently, Camargo-Henríquez and Silva (2022) have used Activity Theory to model context starting from conception up to the development of context-aware systems. This model focuses on relationships arising due to interactions between sociotechnical components. Since a human user uses a smart device to interact with other technical components, context modeling must consider the social and technical aspects.

Jagarlamudi et al. (2021) enhance the QoC to include the Cost of Context (CoC), which is the cost of context gathering and processing. This ensures the validation of Service Level Agreements (SLAs) between a context provider and context user (Kouamé et al., 2020).

Djoudi et al. (2022) argue that the non-functional requirements should be part of the context in addition to the functional requirements. The authors list performance, security, and

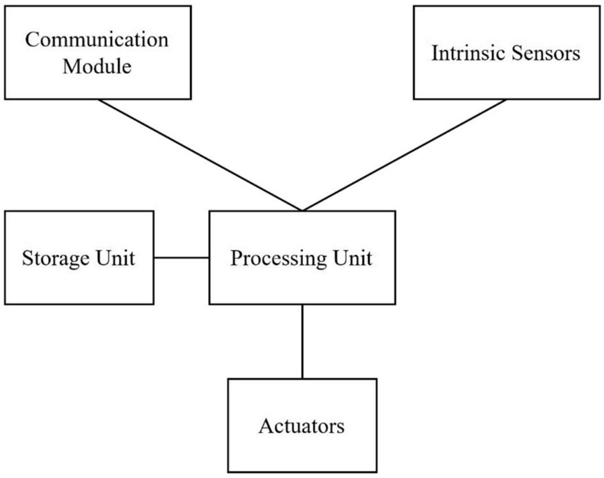

FIGURE 1
A smart device.

availability as examples of non-functional requirements that can be used to describe the context.

Freitas et al. (2021) have considered uncertainty as a constraint on the context and have developed a decision tree to handle the uncertainty. Uncertainty can be considered as a CoC prima facie.

Table 1 presents the comparison of the contemporary literature on context definition and modeling. The comparison facets include the richness of context, QoC, CoC, and power information. Table 1 compares contemporary evidence in the literature based on multiple facets. The context should be rich and capture all elements that can describe it. In the earlier generations of the context-aware system, limited information was captured, resulting in the development of specific context-aware applications. In newer generations of context-aware systems, the concept of QoC is introduced with each contextual element and has now evolved to CoC. However, power consumption information has not been included in the CoC. Power consumption is necessary information that is viewed as a cost of gathering and processing context and becomes suitable in enabling power-constrained context awareness. This study further enhances the CoC by including power information in addition to rich context, QoC, and CoC.

3 Components of an IoE environment

An IoE environment includes sensors, devices, and services. This environment is bounded locally as well and can have a global outreach. The core of an IoE environment is a smart device that communicates with sensors, appliances, and services and provides computation for the classification of context. A smart device has a communication module, intrinsic sensors, a storage unit, a core processing unit, and actuators, as shown in Figure 1. Table 2 describes the functionality of each component.

Consider as an example a handheld smartphone (Samsung, 2020). It communicates using GSM and 4G/5G technology and Wi-Fi and Bluetooth. Accelerometers, GPS, pedometer, gyroscope, etc. are the intrinsic sensors. The storage is provided by using flash memory external SD/micro-SD/nano-SD cards and n-core processors. The actuators are the screen and the speakers. In the case of a smart washing machine, Wi-Fi, weight sensors, processor, register memory, and machine and buzzers are examples of communication modules, intrinsic sensors, processing unit, storage unit, and actuators, respectively (Samsung, 2017).

The sensors generate perceptions which are then mapped onto actions. A history or perception leads to the percept-action sequence shown in Equation 1 (Russell and Norvig, 2010). AI-based systems exhibit percept-action functionalities that correspond to IF-THEN-ELSE constructs in programming environments. This presents a simple AI-based system as a rule-based system (RBS).

$$P^* \rightarrow A \tag{1}$$

If the mapping of perception onto actions is a case of classifying a context into several known categories of context, Equation 1 can be redefined as shown in Equation 2. The $\rightarrow_C$ is the mapping based on a supervised classification algorithm.

$$P^* \rightarrow_C A \tag{2}$$

An assortment of gadgets that a user owns or controls temporarily constitutes a smart personal space. Multiple smart gadgets, including handheld and wearable ones, may be owned by one user. These devices include laptops, smart phones, tablets, smartwatches, fitbit, and smart health monitoring devices. These gadgets are referred to as smart personal spaces since they may be controlled by a user. A smart personal space also contains the user's private and public data. This information can be kept up to date locally or remotely over the Internet.

The data of a user grow exponentially and are required to be protected against privacy vulnerabilities (Poelker, 2013). The data are generally replicated across remote services, creating an ownership conflict. Social Linked Data (SOLID) facilitate the creation of a personal online data store (POD) that ensures ownership and privacy using access control lists (ACL; Berners-Lee, 2021). The POD provides an abstraction to the users' data. The data can be stored in files, relational databases, and non-relational databases. Figure 2 shows a model of a personal smart space.

Multiple smart spaces interacting with appliances and remote services create an IoE environment (Mahmud et al., 2020). This is equivalent to having several patients in a hospital, several people living in the same house, engineers in a laboratory, or coworkers in an office. Multiple smart personal spaces, appliances, and remote services all communicate with one another in an IoE Environment. Conflicts in access may occur because many personal spaces use the same channel to communicate with the services. Remote services and appliances can prioritize service delivery by using a distributed conflict resolution method. Figure 3 shows a model of an IoE environment.

A collection of IoE personal spaces interacting with local appliances and each other is termed a smart environment. A smart

TABLE 2 Description of components of a smart device.

Component	Description
Communication module	This module uses Wi-Fi, Bluetooth, Zigbee, GSM, or 4G/5G/6G technologies to communicate with other devices, services, and appliances within an environment. It is also able to communicate with remote services via the Internet. This module also communicates with external sensors. A software-based communication mechanism using Sockets, Request-Reply paradigms, RPC, and Java RMI is implemented (Coulouris et al., 2011).
Intrinsic sensors	The onboard sensors connected via the internal circuitry of the device are termed intrinsic sensors. Among various enabler systems, Raspberry Pi and Arduino are widely used in different applications (Arduino, 2021; Raspberry Pi Foundation, 2021).
Storage unit	A storage unit is used to store programs and data (Hennessy and Patterson, 2012). Among many different technologies available, ROM, RAM, Flash memory, SSD, and mini/micro/nano SD cards are used (Stallings, 2016). This is also used to store history information (Malik et al., 2009). The history is stored using relational databases, non-relation databases, and open standards using eXtensible Markup Language (XML) and Web Ontology Language (OWL; Mahmud, 2016).
Processing unit	This is the core of a smart device that uses multicore processing units. Multicore processors can execute threads simultaneously. The processing unit processes sensor data, classifies context, and generates recommendations using machine learning techniques (Mitchell, 1997). This unit is also termed the Context Inference Engine which classifies the current context, gathered via sensors, based on the history of interaction (Mahmud and Javed, 2014). The task of the processing unit is to map input gathered from the sensors into rational actions performed by the Actuators.
Actuators	Actuators perform the actions recommended by the Processing Unit. This may be a simple case of raising an alarm, contacting a physician in an emergency, or gathering students for an online meeting. This unit also arbitrates among alternative services, based on the context.

FIGURE 2
A smart personal space.

environment provides a gateway within the IoE environment; the gathered data are termed context which is used to infer an activity or multiple activities within an IoE environment. This concept is like the data, information, and wisdom hierarchy (Giarratano and Riley, 2004). IoE environments are viewed from three overlapping perspectives (Sezer et al., 2017). The Internet-oriented vision, views an IoE environment from the perspective of seamless connectivity, the Things-oriented vision, views an IoE environment as amalgamation and interaction of different types of devices and appliances, and the Semantic-oriented vision, views an IoE environment as a semantic activity or situation due to the interaction between multiple personal spaces and remote services.

An IoE environment is primarily a distributed system that supports mobility. IoT is concerned with connecting multiple sensors to a microcontroller that senses data and then transmits it over the cloud for computation. This essentially creates two layers, the Fog and the Cloud. Traditionally, Fog is concerned with perceptions and actions while mapping and computation are carried out on the cloud. The Internet of things (IoT) has evolved into the Internet of everything (IoE), where devices, sensors, and appliances are all connected and computation is done within the Fog due to the advent of the system on chip (SoC)-based Fog environment. The IoE world has evolved into an Artificial Intelligence of Things (AIoT) with a stronger reliance on Fog for processing, mapping, or learning functions. The localized processing and reduced bandwidth usage for cloud storage distinguish IoE from AIoT. AIoT is comparatively smarter and can offer big data and machine learning abstractions. Hassani et al. (2018) have proposed that the context can be implemented as a service feature as a part of an IoE environment. A context management platform (CMP), which is in charge of context processing and providing it to context consumers, processes the context.

4 A mathematical model for green context-awareness

While the literature shows that the context is based on a philosophical perspective, the evidence is domain-oriented. This is because the purpose of context awareness is the facilitation of human–machine interaction. Furthermore, the concept of QoC is a misnomer. While it appears that it is the quality of the context, it is essentially the quality of contextual information which is a subset of context.

In addition to this, the QoC is limited and does not cater to the energy or power used to gather and subsequently process the context (Mahmud et al., 2018). A context-aware system is

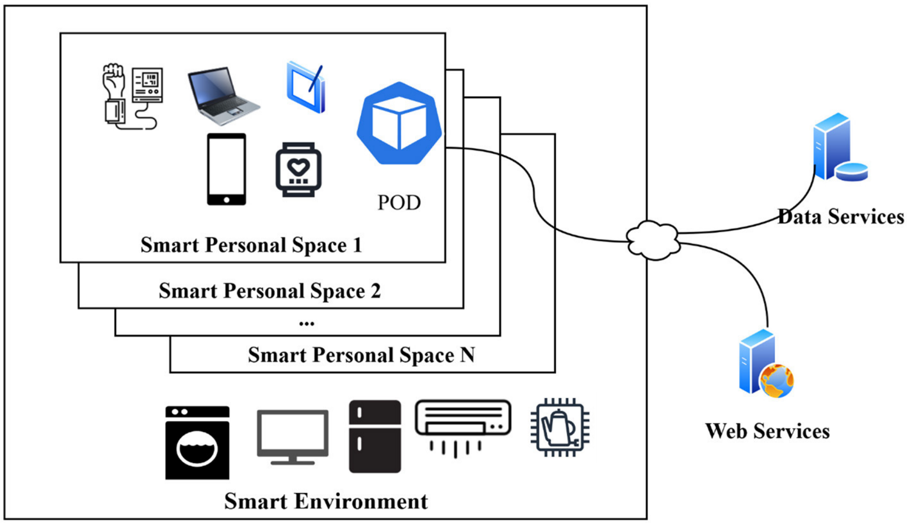

FIGURE 3
An IoE environment.

part of an IoE environment. An IoE environment has battery-operated and mobile devices (Mahmud et al., 2020). Context gathering and processing are constrained by both limited battery and noisy wireless connections. While the parameters of QoC show whether individual contextual information is useful or not, power is considered at the complete context level. On a simple level, it means how much power is consumed when the context is gathered and subsequently processed. This could be used as a metric for CoC as well, where a higher power consumption during context gathering may defer the context processing (Mahmud and Hussain, 2022a,b). This might require a history of contexts to be maintained (Malik et al., 2009). The history can be used to defer context gathering as well.

Rosa et al. (2015) highlighted the importance of context histories as an ingredient for context classification. The past and current contexts of the users help in improvement. Context histories record context information using temporal indexes. The context is thus a collection of sequential patterns stored in relational databases (da Rosa et al., 2016). This sequential pattern supports context prediction using stochastic processes. The size of previous contexts leads to the Big Data view of context-aware systems (Dinh et al., 2020). This entails precise results but at the cost of space. Histories are useful for understanding repeating processes and trends, specifically in the areas of human interaction and social sciences, and have been used for cultural heritage applications (Michalakis and Caridakis, 2022).

Traditionally, once the context is processed, situation is classified using machine learning techniques. The classified situation becomes an activity label of context with an associated confidence value (Mahmud and Javed, 2012, 2014). These techniques use rule-based approaches and classification-based approaches to classify the context. From fuzzy learning to Bayesian learning, Hidden Markov Models, and Convolutional Neural Networks, researchers have utilized many algorithms to classify the current context (Chui et al., 2023; Saleem et al., 2023). This current context requires a history that records previous contexts and their classification outcomes. The classification outcome is given a label or an activity label in the case of human activity recognition or human context. Since, the context classification utilizes a machine learning algorithm, the precision of the classification outcome is dependent on the context history and the algorithm used. This outcome is then subjected to confidence in the outcome. For example, a multi-class context classification algorithm using Artificial Neural Networks (ANN) could classify the context into multiple classes and select the one that has the highest probability or confidence. Confidence is a measurement of the effectiveness of the context classification algorithm and is a floating-point value between 0 and 1. It can be calculated based on multiple sets of training data and test data for the classification algorithm.

Filippetto et al. (2021) have used similarity measures to classify contexts based on the context histories. The mechanism requires a context history that contains records of project management activities. The context histories are compared with each other to find similarities. This similarity analysis includes risk similarities and project description similarities that are subsequently used to generate recommendations.

The classified context is given a label. When context belongs to a human, it can be classified as an activity label. The activity label can be used to discover services, adjust SLAs, or perform some actions. For example, in the domain of smart healthcare, the context of the patient would be classified into activity labels or health states. These can be used to raise alerts, inform caregivers, or dispatch emergency services. Similarly, for a commuter, the context could be classified, and a music playlist delivered to enhance their mood and reduce symptoms of depression and anxiety. The music playlist can be generated from a variety of online music playback services.

A context is associated with an appropriate label, which is then used to perform appropriate actions. In general, the context is associated with a label which is the classification outcome; a context could have a distinct label, while a label can have different contexts.

A label is associated with a confidence value that describes the precision of the classification outcome.

An activity can trigger multiple actions. These actions could also be adjustments in SLAs or service negotiations. More than one activity can be triggered based on an activity label. This leads to the question that whether the action should be part of the context. Since the philosophical perspective includes everything as part of the context, it appears logical to include the actions as part of the context. The classification of the context and subsequent action takes non-zero time. This entails that a context record would include all information within a time window.

With the aspects mentioned earlier, the authors present a mathematical model of context with emphasis on the richness of information that includes power information as CoC and actions performed as part of the context. The model is presented using the basic mathematical concept of set theory. While researchers have used advanced concepts of ontology and mereotopology, set theory aptly describes the nature of context and is easier to understand and convert to programming constructs. A context c is defined by a finite set of attribute-value pairs or contextual data. The contextual data are gathered from using intrinsic sensors, termed sensor data S, and deduced through remote services, termed deduced data D. However, to gather the latest information, the deduced data are deduced using the latest value of sensor data. To better understand the context c, let us assume that it is gathered by using sensors embedded in a smartphone. Here, a context-aware system is installed in the smartphone that can classify the context. The attributes include the sensors embedded in the smartphone including a GPS sensor that records latitude, longitude, and altitude. These three attributes are part of sensor data S. The latitude and longitude can be used to access a location service to deduce the location, for example, home, university, and office. The location information is part of the deduced context D. Both the sensor data and deduced data are part of the context c. Equation 3 represents the context c mathematically, where there are n number of sensor data elements S and m number of deduced data elements D.

$$c = \{\{S_1, S_2, \cdots, S_n\} \cup \{D_1, D_2, \cdots, D_m\}\} \tag{3}$$

Each contextual element l in the set of context c has an associated QoC value. These include accuracy a, freshness f, and trustworthiness tr. The accuracy represents the accuracy of measurements, and this could be represented using a floating-point number normalized within a range of $0 - 1$. A high accuracy will be given to the values provided by the GPS sensor when a person uses their smart device outside in the open, while within a building, the accuracy would be low. Freshness refers to the time when the sensor provides the data. A high freshness means that the value was sensed relatively soon in the past. This is necessary if a person using their smart device is walking or traveling in a bullet train. While walking, a GPS value would not change as fast as in a bullet train it would change. Furthermore, while GPS data might be relatively fresh, the deduced weather information would have different implications with low freshness. The freshness is also a normalized floating-point value between 0 and 1, where 1 has higher freshness. Trustworthiness refers to the trust value and is useful for deduced data. Trust is a normalized floating-point value between 0 and 1, where 1 signifies total trust. Data from embedded sensors have a higher trust value, while deduced data and data from nearby services have a lower trust value. Trust is evolved over time after each interaction between a user's smart device and remote services.

More QoC parameters can be included as well. Any contextual element l within the context c can be represented as $\mathbf{f,_a^{tr}l}$.

The classification of context c assigns an appropriate activity label with a corresponding confidence d. Confidence is the value that shows how well the classification outcome has been reached based on the performance of the classification algorithm during tests. Each activity label has multiple actions A that can be performed as shown in Equations 1, 2. The actions could include delivering a music playlist, alerting a caregiver, or recommending nearby restaurant deals. The actions selected are part of the situational context C. The difference between context c and situational context C is that c is the context prior to context processing and C includes o number of action A, confidence d, and power information p as a CoC parameter. Moreover, while the current context c is one record that includes the sensor data and deduced data, it is not complete unless it has been utilized. This means that once the context c has been classified, and actions have been performed based on the classification outcome, the context, classification outcome, the actions performed, the confidence in the classification outcome, and the power consumed during the complete process are appended to the context. This means that context c is a subset of situational context C. Mathematically, the relation between context and situational context is $c \subseteq C$. The power information p includes the power consumed during the complete context processing, starting from context sensing. Power consumption leads us to understand how much power is consumed in the processing context so that it can be conserved by employing green classification algorithms or through green context processing. The confidence d and the power information p are singleton set in the situational context C. The confidence is a normalized floating-point value between 0 *and* 1 that represents the confidence in the classification outcome. The power information primarily represents the total power consumption of the context process. This is a single value that can be depicted in milliwatt (mW). Both power information and confidence are the aspects of CoC that allow us to improve the context processing.

Equation 4 shows the situational context C. In Equation 4, there are n number of sensor data, m number of deduced data, and up to o number of actions performed once the context is classified.

$$\begin{aligned} C = \{\{S_1, S_2, \cdots, S_n\} \cup \{D_1, D_2, \cdots, D_m\} \\ \cup \{A_1, A, \cdots, A_o\} \cup d \cup p\} \end{aligned} \tag{4}$$

It can be observed that the situational context C is represented as a union of unions, showing the complexity of context. The power information p is the power consumed in watts for gathering and processing context C. Equation 4 can be represented as a union of the union in Equation 5. It is interesting to note that confidence d and power information p are both singleton sets. In Equation 5, there are n number of sensors and m number of deduced data,

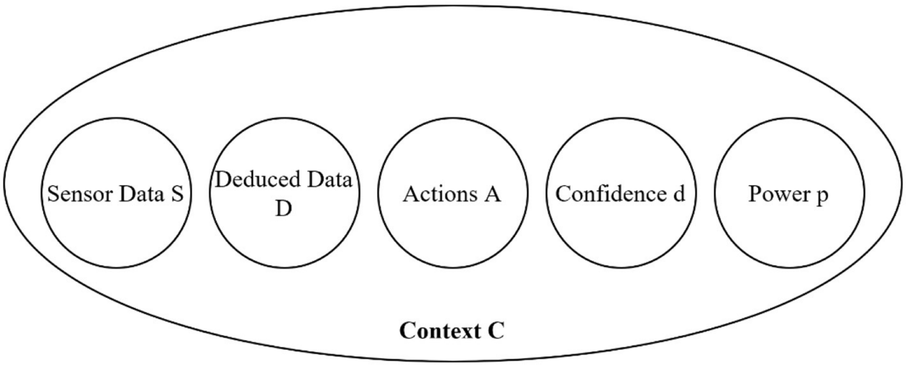

FIGURE 4
Graphical representation of the context.

and after classifying the context, up to o the number of actions can be performed.

$$C = \left\{ \bigcup_1^n S \cup \bigcup_1^m D \cup \bigcup_1^o A \cup d \cup p \right\} \tag{5}$$

Figure 4 shows the concept of context with power as a measurement for CoC. The context is a union of all sensor data, deduced data, actions performed, and confidence in those actions. The power is the cost which is measured as the power consumed in the constructing context.

It's the inception context has been suggested by pioneer researchers to be rich and inclusive. However, various systems that have been developed define context based on the domain. Moreover, this leads to multiple context-aware systems working effectively on a person's smart device and interacting with sensors and remote services but unaware of other context-aware systems. There is a need to develop a single context-aware system that assists a user in their mundane activities by accessing and adjusting remote services based on the context. This requires a rich context that is all-inclusive, which requires both sensor data and deduced data. This is then processed and mapped onto the situational context. The classification outcome and the actions performed by the context-aware system are also recorded within the situation context. Since the way forward is a single context-aware system, there could be multiple actions, for example, setting the AC temperature based on patient data and, concurrently, alerting a caregiver. Furthermore, if the power information is included in the situational context, it can be used to conserve power and energy.

5 Case study for proof of concept

To explain the effectiveness of the above model, an example case is selected. The authors of this study have developed an Android app to facilitate contextual information gathering (Mahmud et al., 2022a). The dataset is collected and then used to train machine learning-based models of context awareness. The app gathers the data of sensors embedded in a smartphone. The sensors include GPS, accelerometer, ambient light, average current, voltage, and others. Data from the GPS sensor are provided in latitude and longitude. This is then sent to multiple online web services, which provide weather information and address information. The address and weather information are both deduced data. The gathered context is then processed to classify the activity label with a degree of confidence. Depending on the context of the user's choice, appropriate actions are performed. The PowerIpsum dataset holds records as attribute-value pairs. Such a dataset allows the use of probabilistic techniques including Bayesian classification, Markov Chain, and ANNs, and other ensemble machine learning techniques, to classify unknown instances. The dataset comprises multiple records. The users have used their smartphones to log the records. Each record includes the contextual data and the associated label. Users have used different Android-based smartphones to gather data. For the purpose of this case study, a single record has been used to represent and store the context, according to the proposed method in Section 4.

Table 3 shows a snapshot of the context. This case study assumes that a user has a single smartphone to interact with services.

As shown in Table 3, the snapshot of the contextual data can be modeled using the mathematical model proposed in this study. Using Equation 3, as shown in Table 3, the context that represents the snapshot can be quantified as shown in Equation 6.

$$C = \left\{ \begin{array}{c} \left\{ \begin{array}{c} 162856121,\ 104.21,\ -43.12,\ -10.15, \\ -1.29,\ 6.87,\ 7.22,\ 1501,\ 0.35,\ 3.26, \\ -0.7,\ 33.58327,\ 73.08341,\ 453,\ -45.6,\ -15.24, \\ -7.32,\ 48.63, \\ Good,\ 72,\ 32,\ 3910,\ Discharging,\ Li-ion,\ 394, \\ 61,\ 5 \end{array} \right\}, \\ \left\{ Rainy,\ Rawalpindi \right\}, \\ \left\{ Silent,\ DND \right\}, \\ \{0.2\}, \\ \{1.54\} \end{array} \right\} \tag{6}$$

Equation 6 represents a single record or instance as part of a context history, which is composed of many contexts C. Equation 6 is a union of union that represents C as quantified in Equation 4.

TABLE 3 A snapshot of context.

Contextual information	Sensor	Type	Description	Value
Timestamp	CLK	Sensor data	This is a timestamp of the record	162,856,121
Azimuth	Orientation sensor		Azimuth of the device	104.21000
Pitch			Pitch of the device	−43.12000
Roll			Roll of the device	−10.15000
X Acc	Accelerometer		Acceleration along x-axis	−1.29000
Y Acc			Acceleration along y-axis	6.87000
Z Acc			Acceleration along z-axis	7.22000
Lux	Ambience		It measures the ambient illuminance in lux	000001501
X Angular Vel	Gyroscope		Angular velocity of the device's rotation along the x-axis	0.35000
Y Angular Vel			Angular velocity of the device's rotation along the y-axis	3.25500
Z Angular Vel			Angular velocity of the device's rotation along the z-axis	−0.70000
Latitude	Location sensor		Latitude of the device	33.58327
Longitude			Longitude of the device	73.08341
Altitude			Altitude of the device	000000453
X Strength	Magnetometer		Magnetic field strength along the x-axis	−45.60000
Y Strength			Magnetic field strength along the y-axis	−15.24000
Z Strength			Magnetic field strength along the x-axis	−7.32000
Abs Strength			Absolute strength of the magnetic field	48.63000
Healt	Battery extension		Health status of the battery	Good
Level			Battery level as a percentage of total capacity	000000072
Temperature			Temperature in Celsius	000000032
Voltage			Voltage in milliVolts (mV)	000003910
Status			Status i.e., charging or discharging	Discharging
Technology			Technology of the battery	Li-ion
Current			Current draw in milliampere (mA).	−000000394
Humidity	Hygrometer		Humidity in the environment	000000061
Distance	NFC sensor		Measures the NFC of a compatible device	000000005
Weather	Weather WS	Deduced data	Gives the outlook of the weather	Rainy
Address	Location WS		Gives the address of the location	Rawalpindi
Activity	-	Label	The activity label of the context	Research work
Confidence	-	Confidence	Confidence in the classified activity label	0.20000
Actions	-	Action set	The set of actions performed	Silent, DND
Power	-	Power	Power consumed	1.54000

As can be observed, the first element in Equation 6 conforms to the set of sensor data S, which are gathered through onboard sensors. The second element is the deduced context D, representing weather and location label. This has been deduced by sending the GPS information, which is sensed through the GPS sensor module, to remote weather and location services, as shown in Table 3. The third element represents the action performed in the recorded context. The actions are performed once the context is classified using a machine learning algorithm.

The classification outcome is then used to perform actions which are then recorded in the context C. The next element is confidence d on the classification outcome and finally, the last element contains the power consumed in milliwatt. Equation 6 is a single record in the history of context that is maintained in a context-aware system. The sensor data, deduced data, the classification outcome, and the power consumed compose a single record. A collection of these records is used to classify an unknown context by employing machine learning techniques.

The power information can be used to determine whether, for the given state of the battery, the context should be gathered or deferred until the battery power is sufficient. In this case, the

TABLE 4 Snapshot of context using features proposed by Unger et al. (2018).

Contextual information	Sensor	Type	Description	Value
Latitude	GPS	Sensor Data	Latitude of the device	31.25N
Longitude			Longitude of the device	34.78E
Part of week	CLK		Part of the week	Midweek
Time of day			Time of day	Day
Ringer mode	Ringer		Ringer mode of the device	Vibrate
Light	Light sensor		The ambient light in lux	1,598
X Acceleration	Accelerometer		Acceleration along x-axis	2.21
Y Acceleration			Acceleration along y-axis	0.87
Z acceleration			Acceleration along z-axis	0.10
Pitch	Orientation sensor		Pitch of the device	12.10
Roll			Roll of the device	0.10
Skewness			Skew of the device	0.01
Noise level	Microphone		Noise level of the surrounding	Low
Screen on 20	Screen state	Deduced data	Percentage of time screen was on in last 20 min	50
Screen on 10			Percentage of time screen was on in last 10 min	20
Screen on 1			Percentage of time screen was on in last 1 min	80
Average duration	Call state		Average duration of calls as a percentage in the last 20 min	10
Count			Count of calls	2
Number of bytes	Application traffic		Number of bytes sent and received	20,340
Number of packets			Number of packets sent and received	56
Gestures	Gravity sensor		Infers complex gestures and motions	Swing
Activity	Android service	Activity label	Activity of the user	Walking
Confidence		Confidence	Confidence in the recognition	0.9
Weather	Weather service	Weather API	Weather of the surroundings	Sunny
Battery level	Battery	Power information	Battery level in percentage	60
Battery temperature			Temperature of battery in Celsius	26
Battery Status			Status of battery	Discharging

actions stored in the context history can be performed if the context can be correctly predicted, conserving power. Equation 7 gives a rule that defers context gathering based on the power information, where if the battery level is <5%, context is predicted without gathering contextual data and carrying out context processing. This can help in saving power since most of the power is consumed in communication and processing. Given the state in Table 3, the context would be gathered, and no power would be conserved.

$$\begin{aligned} &IF\ (BatteryLevel \leq 05) \\ &THEN\ predictContext\ (\,);\\ &ELSE\ gatherContext(\,); \end{aligned} \tag{7}$$

Further rules can also be developed and adapted to better satisfy the needs for a context-aware application. The amount of time taken to gather the context and the current battery state can both be considered to implement complex rules, as shown in Equation 8. If the battery level is <10% and the power consumed in gathering sensor data is <2 milliwatts, the system can carry out context awareness and context processing, as shown in Equation 8.

$$\begin{aligned} &IF\ (BatteryLevel \leq 10\ \&\&\ PowerConsumed\ \leq 2) \\ &THEN\ gatherSensorData\ (\,);\\ &ELSE\ predictContext(\,); \end{aligned} \tag{8}$$

In Equations 7, 8, power information can be used as a CoC to support decisions. These decisions would result in power conservation and will enable Green Context Awareness (GCx). The power information had not been recorded or utilized as evident in the literature; as shown in Table 1, the CoC would not be utilized, and a context-aware system would become power-hungry.

Unger et al. (2018) have also selected features to define a user's context and have included battery level as the power information. This is selected as it has associated power information within the context. Table 4 shows the snapshot of context based on the features of context proposed by Unger et al., and Equation 9 represents the situation context for the features selected by Unger et al. Here, the values have been assumed to show the effectiveness of the proposed technique.

$$C = \left\{ \begin{array}{c} \left\{ \begin{array}{c} 31.25N,\ 34.78E,\ Midweek, Day,\ Vibrate,\ 1598, \\ 2.21,\ 0.87,\ 0.10,\ 12.10, \\ 0.10,\ 0.01, \\ Low \end{array} \right\}, \\ \left\{ 50,\ 20,\ 80,\ 10,\ 2,\ 20340,\ 56,\ Swing \right\}, \\ \left\{ walking \right\}, \\ \{0.9\}, \\ \{60,\ 26,\ Discharging\} \end{array} \right\} \quad (9)$$

The situation context in Equation 9 shows that the proposed technique is suitable for all available datasets with some variations. Here, in Equation 9 and Table 4, the actions performed are not listed, and the power information is given as a battery state with no information of how much power was consumed. The power information here is a set of battery level, battery temperature, and status of the battery. While this is power information, it lacks a critical component of how much power was consumed during context processing.

To confirm the effectiveness of the work presented in this study, the context formulation, as shown in Table 3 and Equation 6, is compared with the evidence in the contemporary literature presented in Table 1. Table 4 presents the effectiveness of the work presented in this paper as compared with the literature. The comparison is based on whether power information as shown in Equation 6, can be included in context and be used as CoC, and specifically, if the rules given in Equations 8, 9 can be implemented for each evidence in the literature.

Table 5 shows that the power information can be represented as CoC within the context based on the work presented in this study. Thus, this power information enables the firing of rules that implement power-constrained context awareness.

TABLE 5 Effectiveness of work presented in this paper vs. evidence in the literature.

Related work	Power information as shown in Equation 6 can be included in context and be used as CoC	Rules in Equations 8, 9 can be implemented
Schilit et al. (1994)	✗	✗
Brown (1995)	✗	✗
Abowd et al. (1999)	✗	✗
Dey (2001)	✗	✗
Zhu et al. (2018)	✗	✗
Riaz et al. (2005)	✗	✗
Bazire and Brézillon (2005)	✗	✗
Sheng and Benatallah (2005) and Sheng et al. (2009)	✗	✗
Mahmud et al. (2007a,b)	✗	✗
Buchholz et al. (2003)	✗	✗
Manzoor et al. (2008)	✗	✗
Camargo-Henríquez and Silva (2022)	✗	✗
Klimek (2022)	✗	✗
Thi et al. (2022)	✗	✗
Jagarlamudi et al. (2021)	✗	✗
Kouamé et al. (2020)	✗	✗
Freitas et al. (2021)	✗	✗
This paper	✓	✓

6 Conclusion

The traditional definition of context is centered on the richness of context to describe situations. Each situation is classified, and an appropriate label is deduced by a context-aware system. The label is the classification outcome of the classification algorithm used in context processing. Actions suitable for each label are carried out by the context-aware system within an IoE environment. There can be multiple actions that facilitate the mundane activities of a user. In the case of users, the labels describe the activity of the user and are termed activity labels. The philosophical basis of the context demands that everything that can be used to describe a situation should be a part of the context.

This includes sensor data, deduced data, actions performed, and the confidence on the classified activity label. The confidence comes from the effectiveness of the classification algorithm over test data. In addition to these, non-functional aspects should also be included within the context as the CoC, which are the quality parameters of the context. This study presents a mathematical model of context based on the philosophical perspective of context. The authors have presented a rich, mathematical model using the set theory that includes sensor data, deduced data, actions performed after activity classification, confidence in activity classification, and the power consumed during context processing as a CoC. This model is domain-independent and also enables QoC parameters for each context element. This allows the development of a unified context-aware system that facilitates a user in all activities. Since the context is gathered using battery-operated smart devices, it is necessary to conserve energy. To conserve, the consumption should be measured. Here, within the context, the power information is included in the context. This leads to an evolution of the context in an IoE environment, where the sensor data and deduced data are aggregated to form the context. This context is then processed, and classification outcome, confidence, set of actions, and the power information are appended to the context, thus creating the situation context. The context is a subset of the situational context which includes CoC elements.

For experimental results, context gathered using the app PowerIpsum is represented mathematically, and as part of the context, the power information is used as a CoC metric for deferring context processing, thus conserving power. The embedded sensors enable measuring power consumed and can be used to measure energy consumption as the context processing takes non-zero time. This is the first step toward energy conservation that could be achieved by developing rules to enable power-constrained context awareness.

For future work, the CoC needs to be expanded to include more non-functional metrics that can be used to execute constrained context-aware systems. The case study that has been included to support the claims assumes a single smartphone as a user's device. Currently, multiple devices have not been included in the proof of context. The complications and complexity of multiple devices for a single user are left for future work.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

UM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. SH: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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