Context Management Life Cycle for Internet of Things: Tools, Techniques, and Open Issues

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ABSTRACT

The advent of the Internet of Things (IoT) and the concomitant development of smart systems has rendered context-aware computing an emerging field of research. The IoT facilitates the large-scale integration of Machine-to-Machine (M2M) communication systems, largely independent of human intervention. The context of a situation, encompassing factors, such as mood, location, and activity, is typically taken into account by humans in an implicit manner, influencing their subsequent actions. Similarly, IoT based smart systems require context data acquired through the use of sensors. The primary challenge lies in the adaptation of context information through the proper modeling and analysis of the vast and heterogeneous sensor data. The phases of context acquisition, modeling, reasoning, and dissemination are collectively referred to as the context management life cycle. The principal aim of this paper is to provide a comprehensive overview of the current state of the art in each phase of the context management life cycle. This study presents a comprehensive review of the tools, techniques, algorithms, and architectures documented in the relevant literature, with a focus on research papers and articles published between 2010 and 2024. The discussion and open issues section at the end of the paper offer insights for future researchers engaged in the study, development, implementation, and evaluation of techniques and approaches for context management in IoT.

Keywords-IoT; context aware computing; context acquisition; context modeling; context reasoning; context dissemination

I. INTRODUCTION

The IoT has emerged as one of the most significant and rapidly evolving technologies in recent times. It enables applications to perform automatic identification of objects, facilitate communication, and make autonomous decisions [1]. The evolution of smart environments, including smart cities [2], smart homes [3], and smart healthcare [4], has made the IoT an integral part of individuals' daily lives. The term "smart environment" is defined as a world where sensors, actuators, and computing elements are integrated into everyday objects and interconnected by a continuous network [5, 6]. Context awareness represents an indispensable element of smart systems. Context-aware computing has been a topic of interest for several emerging technologies, including ubiquitous and pervasive computing and ambient intelligence, for several years. Context is defined as any information relevant to a particular instance that can describe the situation of an entity [7, 8] and can be either static, as in the case of a user's profile and preferences, or dynamic, as in the case of the user's location. Another category of context, namely user, system, and environment context, is presented in Figure 1 [7, 9]. The term "context-aware" was first introduced in 1994 [10, 11]. A system that is capable of understanding context and making decisions based on that understanding is referred to as a context-aware system. Context-awareness is also referred to as Context-as-a-Service (XaaS). As indicated in the Cisco annual internet report (2018–2023), the number of devices and connections is increasing at a rate of 10% per year, which is considerably higher than the global population growth rate of 1%. The majority of devices are classified as "smart" due to the presence of sensors and actuators, which facilitate M2M interaction with minimal human involvement. Context awareness is a critical aspect of M2M communication because human beings are capable of considering context implicitly, whereas machines require the implementation of context-awareness explicitly for the purpose of proper decision-making and the ability to react accordingly. For this purpose, it is necessary for things to be able to understand their surroundings and context rules. Context awareness provides the basis for personalized and adapted services. It is often activated by events generated by sensors. Sensor data should be properly collected, modeled, reasoned, and distributed for decision making. Context information management consists of four phases, which are collectively termed as the Context Management Life Cycle (CMLC), as presented in Figure 2:

- Context acquisition: The process of obtaining context data from physical or virtual sensors in its original, unprocessed form, using IoT protocols.
- Context modeling: The data collected are then subjected to a modeling process that expresses the information in a meaningful and standard way.
- Context reasoning: The modeled data are processed to derive high-level context. Sensor data are fused together, pre-processed, and analyzed to provide inference.
- Context distribution: The final stage of the process is the dissemination of context to consumers, which may occur on an on-demand or subscription basis.

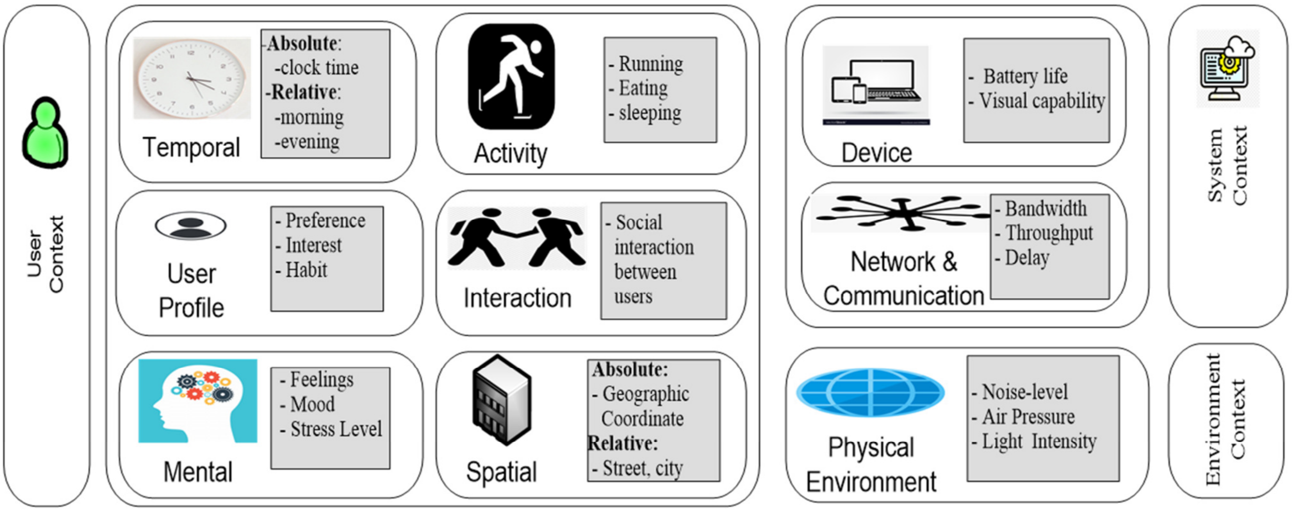

Fig. 1. Classification of context.

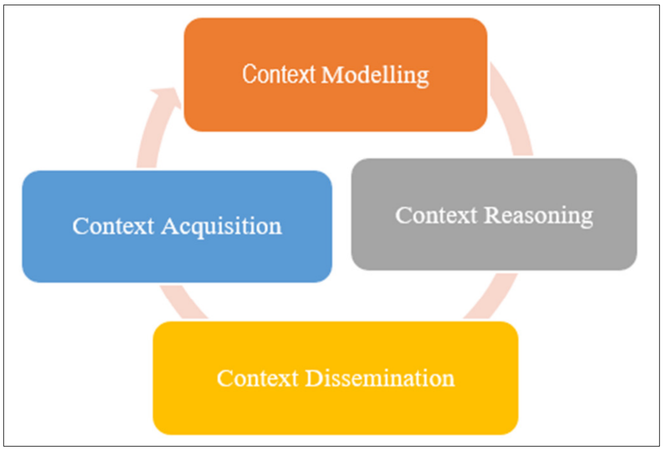

Fig. 2. Context Management Life Cycle.

A number of surveys have been conducted in the field of context-aware computing. The context-aware middleware for ubiquitous computing was analyzed with regard to its modeling, management, reasoning, and provisioning approach [13]. The development and methodology phases for context-aware systems provided the system engineering challenges and techniques [14]. Authors in [15] conducted a review on the historical and conceptual perspectives of context awareness, encompassing ubiquitous and pervasive computing, AmI, and Wireless Sensor Networks (WSNs). Authors in [11] examined 50 context-aware computing projects that were proposed between the years 2001 and 2011. The majority of IoT middleware solutions are devoid of context-awareness functionality. A variety of research avenues were examined, including automated sensor configuration, context discovery, acquisition, modeling, reasoning, and distribution, sensor selection, security and privacy, and context sharing. Significant research has been conducted in the domain of context-aware computing. However, a comprehensive review of each phase of the context management life cycle within the IoT is still a crucial necessity, as evidenced by the existing literature. The present paper presents a discussion of platforms and middleware for context acquisition, modeling, reasoning, and dissemination in IoT environments, along with an examination of the related tools, techniques, algorithms, architectures, and Quality of Service (QoS) attributes.

II. CONTEXT ACQUISITION

The initial phase of the context management life cycle is context acquisition. This phase pertains to the procurement of context from physical or virtual sensors. Context acquisition can be classified according to several criteria, including responsibility, frequency, source, event type, acquisition process, sensor type, or request type. The vast, dynamic, and unpredictable nature of IoT devices necessitates the classification, discovery, and selection of sensors to eliminate redundancy and provide supplementary information for the maintenance of service continuity and reliability.

A. *Research Contributions*

The Context-Aware Sensor Search, Selection, and Ranking Model (CASSARAM) [17] is a model that efficiently identifies the necessary sensors from a large set of sensors with similar functionality. The Context Aware Sensor Configuration Model (CASCoM) [18] is a semantics-driven model that enables the configuration of IoT middleware components. The data may be accessed without a requisite knowledge of the technical specifications of the sensors. The Mobile Sensor Data Processing Engine (MOSDEN) [19] is an IoT middleware designed for use on mobile devices. It is capable of collecting and processing sensor data with minimal programming effort. The Context-Aware Mobile Sensor Data Engine (C-MOSDEN) [20] is a mobile sensing platform that is context- and activity-aware, and which provides on-demand mobile crowd sensing. The Framework for Ambient Services and Event Monitoring (FASEM) [21] is an event-aware, user-centered, and service-oriented framework designed to facilitate the automatic handling of events in ambient environments. The Context-Based Search Engine (COBASEN) [22] is a software framework comprising a context module for defining the semantic characteristics of devices and a search engine for the discovery and interaction with IoT devices. The Cloud-based Publish/Subscribe middleware (CUPUS) [23] is a mobile crowd sensing platform that enables the energy-efficient acquisition of sensor data from mobile devices. The QoDisco [24] is a Quality-of-Context (QoC) aware discovery service comprising an ontology-based model that semantically describes services, resources, and QoE related information. The Portable Discovery Services (PODS) [25] is a generic discovery service framework that is based on the concept that the sensor discovery process can be decoupled from middleware. A Delay-Aware Heterogeneous Cluster-based Data Acquisition (DA-HCDA) technique [26], ensures comprehensive coverage. The Multifarious Sensor-based Cluster Formation Algorithm (MSCFA) is employed for clustering and selecting controllers. The OCDF-IoT is a framework for scalable IoT resource discovery and selection [27]. A Sensing Service Search Model (SSSM) is proposed, comprising two indexing and ranking algorithms that integrate a Heterogeneous Similarity Metric (HSM) with Multi-Criteria Decision Analysis (MCDA) methods. Table I presents a summary of the above research contributions.

III. CONTEXT MODELING

A context model is defined as a behavioral and mathematical description of user context. In the IoT environment, a vast amount of data are collected from a variety of heterogeneous devices, including video streams, images, voice, and strings, which are of different types and formats. The absence of semantics and interoperability renders it challenging for humans and machines to comprehend one another. Context modeling plays a significant role in the IoT context, as it enables the processing of large heterogeneous data sets and facilitates interoperability, while being beneficial for knowledge management, data storage, context sharing, configuration, and maintenance of context information.

A. *Requirements of Context Modeling*

Context modeling must meet certain criteria to be used effectively.

- Richness and completeness: It must include all essential aspects of context that could potentially affect the application.
- Compatibility: It is essential that the context model be compatible with existing, well-defined context models in order to facilitate reuse.
- The capacity to facilitate reasoning: It further enables the generation of knowledge that can inform subsequent decision-making processes.
- Extensibility: In order to facilitate reuse, the approach can be extended in accordance with new requirements.
- Modularity/Granularity: It is essential that the system be highly modular in order to facilitate extension and integration.
- Level of formality: It should facilitate the expression of user requirements in a more natural manner, with the desired constraints.
- Heterogeneity and mobility: It must address the issues of heterogeneity and mobility.
- Sufficiently Expressive: It must accurately represent the real-world objects, context attributes, constraints, and relationships.

B. *Context Modeling Techniques*

The principal techniques employed in the context of modeling are [1]:

- Key Value and Markup Models: Context attributes and their values can be represented as a key-value pair. Markup models employ a variety of marking languages, including XML. The Composite Capabilities / Preference Profile (CC/PP) [29] was the inaugural context modeling approach that employed RDF to represent fundamental constraints [11]. This modeling approach lacks the capacity to effectively represent relationships.
- Graphical: Graphical modeling facilitates the effective representation of relationships and constraints through visual representation, such as the Universal Modeling Language (UML).

- Logic-Based Modeling: It employs a set of rules, expressions, and facts to represent context and offers support for reasoning.
- Multidimensional Context Modeling: The modeling is based on the classification of entities according to their similarity to one another and to other situations. For example, vector space modeling and context space modeling [12]
- An object-role based or object-oriented modeling approach: The modeling approach is derived from database modeling and is based on object-oriented concepts, such as the Object-Relational Database Management System (ORDBMS).
- Ontology-Based Modeling: An ontology is defined as a well-founded mechanism for representing and exchanging structured information. Ontology-based modeling provides expressiveness and interoperability, allowing for easy sharing and reuse, but it is computationally complex [30].

TABLE I. RESEARCH PROTOTYPES, SYSTEMS, MIDDLEWARE AND APPROACHES FOR CONTEXT ACQUISITION IN IOT

Platform	Scalability	Focus	Context Aware	Architectural Complexity	Flexibility/Customization	Tools & Technologies	Limitations
SSSM [16] 2022	Yes	Sensor selection according to heterogeneous QoS values	Yes	Distributed	ND	Python	Lacks dynamic composition of sensing services
CASSARAM [17] 2013	Yes, High	Context-aware sensor search, selection, and ranking model	Yes	Distributed	Yes	Java and android platform	Lacks subscription for sensor& context
CASCOM [18] 2013	Yes	Automate Sensor selection	ND	ND	Yes	Java ,Apache Jena API, Jena TDB	Lacks adaptable sensor level configuration
MOSDEN [19] 2014	Yes, High	Zero programming middleware	No	Lightweight, plug in	Yes, plug in	Java	Lacks context-aware sensing
C-MOSDEN [20] 2015	Yes	Location ,activity-aware mobile on-demand sensing	Yes	Distributed	Yes, remotely configurable,	Android SDK API. Google Nexus 4	Does not provide data analytics capabilities.
FASEM [21] 2015	Yes, High	Dynamic services discovery and selection framework	ND	Semi autonomous	Configuration through rules	ND	Lacks the ambient service classification approach
COBASEN [22] 2015	Yes	Context model and search engine using inverted index	Yes	Distributed	ND	JAVA, PostgreSQL Apache Lucene API	Lacks customized filtering process
CUPUS [23] 2016	Yes	Mobile crowd sensing system	ND	Flat architecture	Yes	ND	Needs integration of components strongly.
QoDisco [24] 2016	Yes, High	Resource discovery with range queries,	Yes	Lightweightde centralized	ND	SPARQL query, Apache JMeter	Not address dynamism and security-privacy
PODS [25] 2018	ND	Fully decoupled middleware solution	ND	Fully decoupled	Dynamic	WireShark Apache Log4j tool	Needs Standard solution for exposing services.
DA-HCDA [26] 2018	Future work	Heterogeneous Cluster-based Data Acquisition	ND	Hierarchical	ND	Network Simulator -NS2	Scalability should be considered
OCDF-IoT [27] 2021	Yes, High	Four-layered Clustering-based Discovery Framework	Yes	Centralized	ND	MATLAB, Protege DL based ontology	Security and privacy issues are not handled

A comprehensive ontology for representing knowledge in the IoT domain is provided in [31]. The ontology comprises seven modules pertaining to the IoT systems and services. Authors in [32] presented a comprehensive, lightweight model combining the SSN and GeoNames ontologies. Authors in [33] developed an ontology model using a top-down design approach to represent both the static and dynamic aspects of user profiles. A context ontology comprising a two-level hierarchy was put forth [34], with the initial level being general and domain-independent. Authors in [35] proposed a chemical reaction-inspired computational model that employs the concepts of graph and reflection.

The Meta-Context Ontology (MCONT) [28] is a generic model, which has been proposed in order to address the challenges presented by dynamic and uncertain context, integrating the use of dynamic Bayesian networks. A standardized solution for the description of things and associated services has been introduced in [36]. The solution employs natural language processing to address semantic interoperability challenges. Authors in [37] proposed an ontology for university activities, with a particular focus on indoor tasks within a university campus, and developed associated reasoning rules. The CameOnto [30] ontology is based on the principles of the 5Ws: who, what, when, where, and why. The proposed ontology is represented through two hierarchical levels: generic and domain-specific. A novel ontological context model [38] was presented for reasoning from a subjective perspective, with five fundamental dimensions—time, location, activity, social relations, and object—considered. InPro is a production workflow ontology based on the 5 M model. Table II provides a brief summary of the above research contributions.

IV. CONTEXT REASONING

Context reasoning can be defined as the processing of sensor data to derive high-level context information and to make predictions or conclusions for the purpose of improving decision-making processes. Reasoning can be categorized into two distinct types, depending on the persistence of the conclusions that are drawn [40]. In the case of monotonic reasoning, the addition of new information to the knowledge base does not affect the conclusions that have already been reached. However, this approach is not well-suited to real-time dynamic systems. In contrast, non-monotonic reasoning allows for the alteration of conclusions based on the incorporation of new information, rendering it a valuable approach for models encompassing uncertainty. In view of the intrinsic uncertainty associated with sensor data in the context of IoT applications, non-monotonic reasoning may prove to be a valuable approach.

A. Context Reasoning Techniques

1) Knowledge Driven Techniques

Knowledge Driven Techniques are model-based techniques, which establish certain prerequisites for the construction of a model. In knowledge-driven techniques, previous knowledge is leveraged to construct a semantic activity model. Case-based reasoning involves the storage of prototype problems, referred to as cases, along with their corresponding solutions. The specific approach employs similarity measures to identify the most pertinent case [41]. Rule-based reasoning is a form of deductive reasoning. The rules are employed for inference, and decisions are made accordingly [42]. Ontology-based reasoning is also referred to as DLR and is a member of the family of logic-based knowledge representations of formalisms. The advantages of these techniques are interoperability, understandability, and adaptability, which are essential for a context-aware environment [43]. Fuzzy logic, also known as approximate reasoning, offers the flexibility to use natural language. Probabilistic logic reasoning integrates the probability theory with the deductive logic. The combination of the two techniques has led to the widespread application of the probabilistic logic across various domains. For instance, the integration of camera images, infrared sensors, and motion detectors has enabled the detection of wild animals in agricultural fields. The Dempster-Shafer theory and Hidden Markov Models represent two prominent approaches within the realm of probabilistic logic reasoning.

TABLE II. RESEARCH PROTOTYPES, SYSTEMS, MIDDLEWARE, AND APPROACHES FOR CONTEXT MODELING IN IOT

Ref.	Domain	Modeling Technique	Main features	Tools	Reasoning Technique	Limitation
[28] 2016	Generic	Ontology and multidimensional	Highly Modular with good maintainability.	OWL	Dynamic Bayesian Network	Lacks relationship of situations with services
[30] 2018	Generic	Ontology	Based on 5ws who, when, what, where and why. Conceptual class: user, activity, time, device, service, location.	Neon methodology, Protégé tool, SWRL	Pellet Reasoner	The effect of context switching with services for real time adaption is not addressed.
[31] 2012	IoT Services	Ontology	Lightweight and complete, Automatic test generation.	OWL ,TTCN-3	Path search algorithm	Lacking temporal and user context
[32] 2012	Generic, Use case location and position	Ontology	Comprehensive lightweight semantic model, QoS and QoI are modeled	SPARQL	Non-logic-based probabilistic service matchmaking	Not considers context of IoT resources, Lacks Service composition
[33] 2012	Generic, Use case: AAL	Ontology	A top-down design for user profile Ontology.	Protégé Tool, OWL	Rule based reasoning	Lacks association between services and user profile
[34] 2014	Generic	Ontology	Semantic approach for context aware services.	OWL	Rule based reasoning	Lacks implementation and evaluation
[35] 2015	Smart check-in , airport scenario	Chemical reflective computing graph model	Chemical reaction-inspire computational model using the concepts of graphs and reflection	Simulation tool S3, JUNG graph library	Chemical Reflective computing model	Due to non-linear efficiency reasoning is challenging for huge data
[36] 2016	Generic	Ontology	Standardized description of things and services in IoT platforms Semantic interoperability	Apache JENA ,wordnet,RDF for rules	Rule based	Focused on only device or thing's context
[37] 2017	University activity ontology	Ontology	location-based service using ontology-based semantic queries	Oracle 11g, OWL OpenGL,rulebase	Rule Based Reasoning	Semantic searchis not addressed.
[38] 2020	Generic,Use case: university	Ontology	Defines three levels (objective, machine and subjective context)	i-log app	Random Forest	Subjectivity in diverse cases should be explored.
[39] 2023	Industrial production	Ontology	Inclusive production workflow with seven ontology modules	Protégé tool, SPARQL	ND	Ontology lacks detailed specification

2) Data Driven (Machine Learning)Techniques

The efficacy of data-driven techniques is contingent upon the availability of substantial data sets used for the training and generation of an activity model. The principal advantage of these techniques is their capacity to accommodate uncertainty and achieve a high degree of accuracy. Nevertheless, data-driven techniques are susceptible to the challenges posed by high-dimensional data and the "cold-start" problem [44]. Supervised learning is predicated upon the usage of a labeled dataset. The process of learning is derived from the training dataset, whereby an algorithm is employed to identify a mapping function that can predict the output for a given input data set [45]. In contrast, unsupervised learning pertains to unlabeled data. The model identifies the pattern and makes a prediction regarding the output. Reinforcement learning is also referred to as semi-supervised learning. The user or application attempts to attain a particular objective, and the user's feedback are provided in the form of rewards and penalties [46].

B. Research Contributions

The Context-Aware Activity Recognition System (COSAR) [47] is a reasoning system that integrates ontological reasoning with statistical inference. A novel variant of multiclass logistic regression has been employed. Authors in [48] presented a computer vision framework that integrates contextual information with tracking data, thereby enabling the construction of a symbolic model of any given scene. Authors in [49] concentrated on a hybrid reasoning technique to derive context information by combining case-based and rule-based reasoning. Authors in [50] put forth a service personalization approach for mobile users that employs semantic technologies and a service-oriented distributed system architecture. Authors in [51] proposed the use of multi-agent defeasible reasoning as a means of addressing inconsistencies in context information, while authors in [52] investigated the potential of semantic technologies for deriving high-level knowledge, proposing the design of a semantic reasoner. Authors in [53] proposed a hybrid context reasoning mechanism to address the inherent uncertainties in the domain of underwater robotics, with authors in [54] developing a framework to recognize context information pertaining to diverse activities and events within the context of a smart home environment. Authors in [42] presented a hybrid reasoning algorithm for activity recognition in a smart environment, combining Web Ontology Language (OWL) ontological reasoning with the Dempster–Shafer theory of evidence. Authors in [55] proposed an integrated approach to situation awareness, which employed Situation Theory (ST) and Context Spaces Theory (CST) to ensure reliable situation inference. Authors in [56] put forth a method for detecting diverse anomalies in smart home operations. An ontology-based framework was developed that integrated probabilistic planning with machine learning within commonsense reasoning [57]. Table III summarizes the aforementioned reasoning approaches.

TABLE III. RESEARCH PROTOTYPES, SYSTEMS, MIDDLEWARE, AND APPROACHES FOR CONTEXT REASONING IN IOT

Ref.	Reasoning technique	Domain	Focus	Tools and Technologies	Context properties	Modeling technique	Limitation
[43] 2017	Ontological reasoning with Dempster Shafer	Smart Home	A reasoning algorithm for handling uncertainty in activity recognition.	Java API called OWL API ,HermiT reasoner	PIR sensors, item sensor,door sensor		Used only embedded sensors
[47] 2011	Ontological reasoning with statistical inference.	Activity recognition in AAL	Used multiclass logistic regression combined with ontological reasoning	Weka4 , a Java-based toolkit, Protege tool	Location	OWL-DL ontology (ActivO)	Only consider location information for modeling
[48] 2011	Deductive and abductive reasoning	video-surveillance	Framework to model scene by tracking data and context	DL Reasoner,RACER,Protégé	ND	DLontology	Needs more refinement
[49] 2012	Combining case-based and rule-based reasoning	Office environment	Hybrid reasoning combining rule-based and case-based reasoning	Jena2 Semantic Web Toolkit and the jCOLIBRI	ND	Ontology OWL	Lacks the user experiments for response quality
[50] 2014	Combination of semantic and rule-based reasoning	Personalized travel assistance	Service-oriented distributed system. & personalization	SWRL.Protégé, Pellet OWL-API	ND	Ontological User Profile Modeling	Requires more comprehensive set of user concepts
[51] 2015	Multi agent defeasible reasoning	Ambient assisted living	Formal modeling and handle inconsistent context	Maude LTL model checker OWL Api Horn clause rules	Time, , memory, communication, Pulse, Sugar , Body temperature	OWL ontology	Heterogeneous multi-context systems needs more attention
[52] 2016	Rule based	Smart traffic	Semantic reasoning system to evaluate different reasoning approaches.	Jena framework, Apache Camel JMS, MQTT25, SQLite	Location, time velocity, sender identification direction	OWL language	Very restricted context lacking background knowledge
[53] 2017	Ontological, rule-based, and Multi-Entity Bayesian	Under water robot management	Modular and distributed	Pellet reasoned, SWRL rules, UnB Bayes tool, Protégé	Thickness, Estimated Size, Weather,location, spreadSpeed, severity	Ontology	Only under water robotic is studied
[54] 2017	Model-driven approach based on ontology.	Ambient assisted living	Data-centric context awareness.Activities deduction using incremental answer set solver.	Contiki OS, UDP, CoAP and Open Mobile Alliance’s (LWM2M)	Light, motion, temperature, contact, pressure, heart rate, respiration, BP	Ontology rules inDL,Extended SSN ontology	Evaluation with more scenarios having more users and activities is required
[55] 2017	CST and Fuzzy STO	ND	Situation awareness based on CST& Situation Theory,	Ontology with CST and O-MI/O-DF	Ontology	ND	Reasoning with uncertainties is missing.
[56] 2020	Hidden Markov Models.	Smart Home	Detect safety attacks based on user behavior	ND	Camera, temperature, humidity,noise.	ND	Used only time of day for condition
[57] 2023	Machine Learning with probabilistic reasoning	Ambient assisted living	Event calculus based ontology and probabilistic common sense reasoning	Orange4Home and SIMADL datasets	Location, activity,time	Ontology	Not consider indirect effects of events on the user’s context

V. CONTEXT DISSEMINATION

The derived context is conveyed to consumers through a variety of dissemination methods, as shown in Figure 3. The process of distributing context to relevant users or applications, either through subscription or on-demand, is referred to as context dissemination. The dissemination of context facilitates the decision-making process, enabling users to take appropriate action. In considering the dissemination of context, key factors, such as scalability, privacy, and QoS attributes warrant particular attention.

A. Context Dissemination Algorithms

Context dissemination algorithms [58] are classified into the following categories:

- Direct Access Algorithms: Upon the initiation of a context request by a user or application, the service discovery process identifies the context provider, subsequently facilitating direct communication between the provider and the requesting application.
- Flooding Algorithm: The provider disseminates context information to all neighboring entities. In the event that the neighbor in question requires the context information, it may be used. Otherwise, it may be disregarded.
- Gossip Algorithm: Context providers disseminate context information only to selected neighbors. Neighbors can also be selected based on contextual factors, such as distance from the source.
- Overlay: This is a subscription-based approach comprising two phases. In the first phase, subscribers' networks are constructed, and in the second phase, context is disseminated to subscribers periodically.
- Hybrid Algorithms: Different algorithms are combined to leverage their respective strengths for efficient dissemination.

B. Context Dissemination Methods

Derived context is distributed to the interested users in a manner that is either systematic, through the use of subscription services, or ad hoc, through the submission of queries. In the context of the Publish/Subscribe method, applications or users may subscribe to receive context information from a context provider. Subscriptions may be either immediate or periodic. In the case of random queries, users send ad hoc queries to the context provider, which responds with the required information. Semantic search enables queries to be entered in natural language.

C. Context Dissemination Architecture

In a centralized architecture, a single context provider disseminates context to all users. However, this approach has the disadvantage that if the connection with the provider is disrupted, communication is completely disrupted. In a decentralized/distributed architecture, context providers disseminate context to selected neighbors, who then relay it to their neighbors, thereby establishing a chain. Gossip or overlay algorithms employ a decentralized methodology. In a broker-based architecture, context providers are required to register with a broker (middleware) in order to specify their capabilities. Subsequently, users send their queries to the broker, which is then responsible for determining the necessary context requirements.

D. Research Contributions

Authors in [59] proposed a hierarchical approach for structuring the components of large distributed networks. A model based on the federation of multiple mobile context brokers was put forth for use in large systems [60]. A hierarchical context dissemination framework [61] that facilitates the aggregation of context at different levels with semantic filtering was proposed. MediaSense [62] is an open-source, scalable platform that provides transparent access to global sensors and actuators with a heterogeneous distributed network. Authors in [63] introduced a context-aware dissemination framework for mobile phone users. They also proposed a dissemination method that uses a communication bus for communication between elements [64], while a semantic filtering was employed for the selection of context. Authors in [65] put forth a dissemination strategy that generates subscription context filters in an automated fashion, thereby facilitating automated network management. The INCOME framework [66] is a content-based system that employs a publish/subscribe methodology and supports QoC levels. Authors in [67] presented a context-aware system designed to provide services based on contextualized information. A scalable dissemination approach for an urban, dynamic environment was proposed using the ACT concept and a dissemination framework was developed to achieve multiscalability through distributed push and pull communication modes [68]. Authors in [69] presented a stream dissemination system using semantic technologies and a heuristic algorithm was proposed for dissemination decision-making [70]. Tables IV and V summarize the research efforts.

VI. DISCUSSION ON CHALLENGES & OPEN ISSUES

The objective of this study is to elucidate the significance of context awareness in the context of IoT applications. The development of context-aware applications remains a significant undertaking, largely due to the intricate nature of the CMLC implementation process. The study identifies and describes the tools, techniques, algorithms, and architectural approaches that are currently available in the field of IoT. The contributions of various researchers in all four phases of CMLC have been subjected to rigorous evaluation. The evaluation offers a wealth of valuable insights. Context acquisition comprises a series of processes, including sensor discovery, indexing, ranking, and selection. The selection of sensors is typically based on quantitative QoS values, with a paucity of methodologies for handling qualitative values. Some researchers have concentrated their efforts on the composition and classification of IoT services [21], yet their approach lacks the necessary adaptability required in a dynamic environment. It has been established that there are numerous approaches to context modeling. However, ontology has emerged as a dominant methodology due to the heterogeneous nature of IoT resources and data [28, 30, 31–34, 36–38]. Ontologies employ well-defined semantics to represent context, thereby facilitating interoperability. In order to derive high-level context, hybrid reasoning approaches are employed [43, 47-50, 53, 55, 57]. Events play a significant role in context-aware systems; therefore, rule-based reasoning [49, 50, 52, 53] is integrated with other reasoning approaches in order to provide more efficient and accurate solutions. It is also important to note that a distributed architecture is emerging as a promising solution for context acquisition and dissemination, with the goal of achieving high reliability and availability. The majority of the aforementioned context dissemination approaches use a hierarchical and distributed architecture [58, 59, 61-68]. However, there is still a need to further explore the issues of privacy and security. A common observation across all phases is that different techniques exhibit distinct strengths and weaknesses. Accordingly, there is a necessity to reframe these methods in order to mitigate their inherent weaknesses. The study revealed a number of issues and challenges. The following challenges require further investigation with the objective of identifying novel and efficient solutions for context management in the IoT:

- The process of identifying sensors in a dynamic, large-scale environment: The dynamic availability of sensors renders them challenging to track. It is crucial to ensure the provision of alternative services when sensors are offline. In some cases, it may be necessary to combine multiple services in order to meet specific requirements. Additionally, the selection of sensors according to heterogeneous QoS values represents a significant challenge.

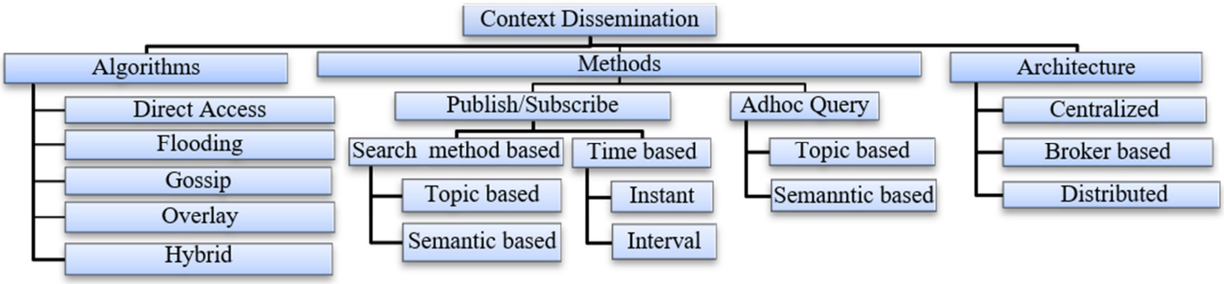

Fig. 3. Context Dissemination.

TABLE IV. FOCUS AND LIMITATIONS OF RESEARCH CONTRIBUTIONS FOR CONTEXT DISSEMINATION IN IOT

Ref.	Focus	Use Case	Limitation
[58]	A scalable approach ensuring completeness and reliability	ND	Missing collaboration of services & providers.
[59]	Hierarchical autonomic network management architecture	ND	Not addressed semantics in context filtering
[60]	A model forlarge scale context-aware system based on federation of multiple context brokers	ND	Lacks handling of topology changes, and congestion control
[61]	Hierarchical and semantic framework	ND	Not implemented and evaluated.
[62]	Scalable and real-time access via heterogeneous network infrastructure.	Object tracking, smart home, health, Energy consumption	Semantic capabilities and data mining techniques should be explored.
[63]	Context-aware data dissemination framework for mobile users in a remote sensing field	Disney World data Hiking	Lacks collaboration among heterogeneous mobile devices
[64]	Uses communications bus, augmented with semantics through the use of ontology	Cloud Infrastructure management	Lacks sharing of core ontology & communication model.
[65]	Automatic context Exchange and generation of semantic subscription filter	Multimedia service management in access networks	Policies need to be defined manually.
[66]	Content-based context data distribution considering QoC	City air pollution	Privacy policies are not addressed.
[67]	Services of contextualized information about IoT devices	ND	Lacks adaptability for dynamic requirements
[68]	Multiscale,QoC and privacy-awareness	Collaborative social welfare	Missing quantitative evaluation
[69]	Stream dissemination system for Semantic IoT	Smart office pilot	Only simple queries are considered
[70]	heuristic algorithm for update dissemination decision	ND	Privacy issues are not addressed

- Standardization in IoT: Despite significant efforts in recent years, the development of a single, standardized middleware solution for context modeling, analysis, and dissemination in the IoT remains a significant challenge.
- Real-Time Analysis of Sensor Data: Flood or fire detection applications require real-time data analysis. Streaming sensor data must be captured in real time. Therefore, due to the highly dynamic environment, the collection and management of real-time streaming data is a major issue.
- IoT big data contextualization: Each stage of CMLC requires extensive data processing. However, most of the research targets small data or specific application. Developing generalized, scalable solutions remains a major challenge.
- Interoperability: The heterogeneity of devices and data in the IoT environment requires semantic interoperability. Therefore, efficient solutions are needed to structure and annotate data and transform them into actionable knowledge [28].
- Context Sharing: IoT sensing is evolving into a cloud service known as "sensing as a service", which allows users to share sensor data based on their needs. The development of specialized IoT cloud services to support this type of sharing is critical.
- Developing learning systems for the IoT: Hybrid methods such as ensemble learning can improve performance; the rise of deep neural networks requires the development of new deep learning algorithms and data analysis techniques.
- Storage Capacity: Challenges related to limited resources must be addressed in context-aware computing.
- Security and trust in the IoT: Revealing user context is a security threat and requires solutions to build trust in

sensors and their data. Balancing strong security with maintaining real-time system performance is a tough challenge.

VII. CONCLUSION

The smart systems require machines to understand the environment and react according to the latter. Due to the advances in sensor technology and the development of smart systems, context-aware computing in Internet of Things (IoT) has attracted the attention of research groups and industries. In this study, context-aware computing in IoT has been reviewed from both conceptual and historical perspectives. Each phase of Context Management Life Cycle (CMLC) was discussed. Different middleware, frameworks, software, algorithms, techniques were studied to identify the encountered challenges, providing researchers with future research directions. The study concludes that more open-source software, architectures, standards, and middleware are needed to address the highlighted issues and challenges for implementing context-aware computing in IoT.

TABLE V. RESEARCH PROTOTYPES, SYSTEMS, MIDDLEWARE AND APPROACHES FOR CONTEXT DISSEMINATION IN IOT

Ref.	Architecture	Algorithm	Method	Protocol	Toolsand Technologies	Context aware	Dynamic	Scalable	Privacy
[58] 2015	Hierarchical	Deterministic overlay	Random query	UDP	Simgrid simulator	Yes	Yes	Yes	Yes
[59] 2010	Hierarchical	Gossip or overlay	ND	ND	ND	Autonomic	Yes	Yes	Yes
[60] 2010	Broker based architecture	Overlay network of distributed brokers	Asynchronous Event based Publish/subscribe	ND	ContextML, CORBA, WSEventing,TIBCO-RV,WebShphere MQ	Yes	Yes	ND	ND
[61] 2011	Hierarchical	Rule-based or neural networks	Publish/Subscribe	SNMP	ND	Autonomic	Yes	Yes	ND
[62] 2012	Distributed System	Peer to peer	ND	DCXP	ND	ND	ND	Yes	ND
[63] 2012	Distributed	Greedy choice algorithm	Hybrid	ND	ND	Yes	Yes	Yes	ND
[64] 2012	Distributed semantic Communication bus	ND	Semantic driven publish/subscribe	ND	OWL,SWRL and JENA	Yes	Yes	Yes	Yes
[65] 2013	Distributed	Semantic subscription filtering algorithm	Publish/ Subscribe	ND	RDF/SPARQL , OWL/ SWRL, Pellet ,Jena 5	Yes	Yes	Yes	ND
[66] 2014	Distributed broker based	Overlay network with filtering	Publish /Subscribe	ND	XML, XPath ,JavaScript	Yes	ND	ND	ND
[67] 2015	Middleware	ND	Publish /subscribe and query	Rest web service	Drools rules	Yes	Yes	ND	ND
[68] 2015	Distributed	Overlay network	Push and pull	ND	XML, XPath JavaScript	ND	ND	Yes	Yes
[69] 2020	Point to point and broadcast	B+-tree Hilber Curve indexes	Semantic, publish/subscribe	ND	ND	ND	Yes	Yes	ND
[70] 2024	Multi Broker	Heuristic forwarding Decision Algorithm	Publish /Subscribe	MQTT	Python 3.8	Yes	Yes	Yes	ND

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