Social Web in IoT: Can Evolutionary Computation and Clustering Improve Ontology Matching for Social Web of Things?

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***Abstract*—Many Internet of Things (IoT) applications can benefit from Social Web of Things (S-WoT) methods that enable knowledge discovery and help solving interoperability problems. The semantic modeling of S-WoT is the main emphasis of this work where we suggest a novel solution, evolutionary clustering for ontology matching (ECOM), to explore correlations between S-WoT data using clustering and evolutionary computation methodologies. The ECOM approach uses a variety of clustering techniques to aggregate S-WoT data's strongly related ontologies into comparable categories. The principle is to match concepts of similar groups rather than full concepts of two ontologies, which necessitates splitting examples of each ontology into similar groups. We design two clustering algorithms for ontology matching using conventional methods, as well as sophisticated clustering techniques. Moreover, we develop an intelligent matching algorithm that uses evolutionary computation to quickly converge to (or ideally identify) optimal matches. Numerous simulations have been conducted using various ontology databases to demonstrate the application and precision of ECOM. Our findings clearly show that ECOM has better results when compared to cutting-edge ontology matching methods. The F-measure of ECOM exceeds 95% whereas it does not reach 90% for all baseline methods. The results also confirm that ECOM scales with big data in S-WoT environments.**

***Index Terms*—Clustering, evolutionary computation, Internet of Things, ontology matching, Social Web of Things.**

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I. Introduction

According to recent market evaluations and studies, the Internet of Things (IoT) real economy size is expected to grow rapidly, with an increase of more than four times from 2018 to 2023, i.e., at a compound annual growth rate of 28.4% over the forecast period [1], [2]. IoT represents a dynamic ecosystem where interconnected smart objects communicate and share data to enable a wide range of applications and services [3], [4], [5], with smart buildings being just one compelling example [6]. The integration of IoT technology in smart buildings enhances energy efficiency, comfort, and security, demonstrating the vast potential of IoT to transform various aspects of our daily lives. Other applications integrating IoT technology including smart transportation [7], and smart grid [8]. In the context of Social Web of Things (S-WoT), a subset of smart devices ("things") acquire social behavior and form social relationships with other items to make it possible to work independently toward a common goal [9], [10], [11].

S-WoT boasts an immense quantity of devices, users, and diverse technologies [12]. This ecosystem facilitates extensive data generation, as these devices and users communicate and producing a wealth of heterogeneous data [13], [14], [15], [16]. Ontologies play a crucial role for structuring extensive datasets that are characterized by multiple relational attributes. These datasets provide the foundational framework for a spectrum of systems, including conversational agents, recommendation engines, semantic search algorithms, and thus enhance the organization and retrieval of complex, interconnected information structures in technological domains [17], [18], and more recently in the domain of S-WoT [19], [20], [21].

There is a need to comprehend various interoperabilities of these ontologies when concepts may be conveyed and represented in different ways by two separate entities [22], [23], [24], [25], [26]. Moreover, ontology matching becomes essential for semantic modeling and knowledge transfer among users and network devices due to the continuous growth in volume and type of heterogeneous data in S-WoT. The process of determining semantic correlations between entities, concepts, and relations is called ontology matching. The goal is to establish a mapping between elements of different ontologies that are equivalent, related, or overlapping in meaning. Ontology matching is an important task in many domains, including data integration, semantic web, and knowledge management. Ontology matching enables interoperability between heterogeneous systems, improves data quality, and supports both knowledge reuse and discovery.

Numerous ontology matching based S-WoT systems have been put forth. Ren et al. [27] defined interaction patterns between IoT devices and semantic modeling of on-device applications to derive more details about applications on devices. Wu et al. [28] developed a space-adaptive network convolutional module that could simultaneously search user interests and social influence propagation mechanisms from S-WoT data. Xue et al. [29] offered a formula to calculate the similarity of two words. The technique determines the cosine distance between two vectors and models linguistic features of words in a given vector space. Without concentrating on one particular information source, the term "embedding strategy" also maintains the rich linguistic content importance of phrases.

He et al. [30] introduced the BERTMap ontology alignment system, which offers support for both unsupervised and semisupervised contexts. The system employs a classifier to predict alignments by adapting the factual embedding bidirectional encoder representations from transformers (BERT) model. Subsequently, the model utilizes ontology structure and logical principles to expand and refine these alignments, thereby enhancing their precision. The aforementioned solutions require similarity computation among concepts and properties of ontologies, which necessitate huge computational and memory resources. This calls for a thorough study of the different correlations and dependencies among features of ontologies using parallel computing and evolutionary approaches [31], [32], [33], which has the potential to intelligently and quickly explore the search space of all possible alignments [34], [35]. This represents the subject of this article that makes use of correlations and evolutionary computation to improve ontology matching processes in S-WoT environments.

A. Motivation

Trivial approaches for comparing two ontologies consider all their properties, which necessitates intensive computational time to handle large amounts of data. Data mining is employed in order to discover and locate promise and inherent data from large databases that cannot be immediately revealed or determined, for example, the association between alcohol and diapers. To study the relationship between different data properties, well-known data mining algorithms such as clustering [36], [37] divide the entire data set into comparable groups. Ontologies have also been subject to clustering through the use of description logic, which separate an ontology database into plentiful components created to analyze connections between ontologies' relevant concepts [31], [32], [38]. Since ontologies are unable to derive even the smallest components from complex ontologies, the aforementioned approaches are unable to directly match disparate ontologies. Furthermore, a more sophisticated and time-efficient approach–such as evolutionary computing, is required to reach a scalable solution. Inspired by the success of clustering and evolutionary computing techniques for dealing with a wide range of difficult problems, this research proposes a novel methodology for ontology matching in the context of S-WoT.

B. Contributions

To the best of our knowledge, this study is the first piece of work that examines clustering and evolutionary methods in-depth for ontology matching in the context of S-WoT. Our principal contributions are listed as follows.

1) Create an innovative solution called evolutionary and clustering for ontology matching (ECOM) to analyze collections of ontologies. This framework combines evolutionary and clustering techniques. The designed framework can be used to significantly improve performance of the ontology matching process in S-WoT settings.
2) Design two clustering techniques for ontology matching that explore both traditional and advanced clustering methods, as well as an intelligent matching algorithm. Instead of retrieving all alignments between ontologies, ECOM benefits from evolutionary computation, which allows finding the best alignments in real time.
3) Extensive simulations have been carried out to evaluate ECOM. The findings demonstrated that ECOM outperforms most complex ontology matching engines.

The remainder of this article is structured as follows. In Section II the subject of ontology matching is explored. The formal formulation of the problem of ontology matching is provided in Section III. ECOM is presented in Section IV. Section V describes the performance assessment of ECOM. Section VI anticipates the future developments of the ECOM design. Section VII provides some concluding remarks.

II. Related Work

A. Semantic Modeling for S-WoT

Rangra and Sehgal [39] considered the problem of identifying communities who are vulnerable to natural disasters and identify the optimal node where the broadcasting system may be located. The authors investigated social media for the purpose of spreading alarming messages, as well as linking WoT with social networks. Zhang et al. [40] created an architecture for recommending smart objects in S-WoT. A BERT with Bi-LSTM network was used in the interest of getting feature vectors for smart objects, as well as an adequate representation of smart object arrays. Wu et al. [28] suggested a novel item recommendation paradigm. The authors explored the propagation mechanism of user engagement and impact on society from S-WoT data simultaneously. To merge user characterizations from both areas, a gating system was also developed. Abdelghani et al. [41] proposed a new multilevel trust model that is dynamic and scalable for S-WoT. The authors suggested multidimensional measures to define S-WoT entities' behaviors. The latter are gathered to use a machine learning-based system that makes it possible for user classification, attack detection, and appropriate countermeasures. In order to propagate confidence throughout the system by exploring fewer resources and maintaining scalability, a hybrid solution was proposed. Magdich et al. [42] denoted a thorough examination of the effectiveness of confidence attack planning when it is incorporated into the trust model, with the goal of precisely identifying node activities in order to assure safe connections of S-WoT nodes.

Ren et al. [27] laid out an approach for scalability of on-device application management across disparate IoT devices. The authors demonstrated how S-WoT can serve to semantically describe the functionality of every IoT system and its interaction patterns. In order to include details about a device's applications, the authors also established semantic modeling for item descriptions. Corno et al. [43] created a search and recommendation system capable of offering relevant contingent rules for use in a variety of settings predicated on a conceptual user's desire. By specifying a set of fundamental S-WoT functionality, users can communicate to a conversational agent their current personalization goal. Chen et al. [44] introduce a brand-new subsumption prediction technique called BERTSubs for ontology web language (OWL) ontology classes. A class's contextual embeddings are computed using the pretrained language model BERT, and special templates are suggested to take into account class context (such as nearby classes) and the logic of existential restrictions. In addition to existential limitations from the same ontology, BERTSubs can also anticipate named subclasses from the same domain or another ontology. Ogunniye and Kokciyan [45] focused on detecting and representing confidentiality in S-WoT in a way that helps privacy assistants better understand their environment. In recent years, the focus has increasingly shifted to technical details of privacy. However, due to the evolving privacy environment, social aspects, such as social trust, also need to be represented. The researchers explored how existing ontologies can be used to represent privacy requirements. The authors also talked about how these conceptual frameworks can be extended with new standards to effectively capture privacy, and presented case studies to show how new requirements can be applied.

B. Ontology Matching

Belhadi et al. [32] developed an ontology matching framework. The optimal qualities for matching ontologies are chosen using data mining techniques in their solution. Furthermore, by looking at various statistical qualities like the mean of quantities for every data attribute, a novel approach of choosing pertinent elements for matching was discovered. Djenouri et al. [46] created a clever framework for matching ontologies in applications related to smart cities. The authors investigate pattern extraction to unearth insights from ideas in ontologies that need to be aligned, then unearth pertinent data to diminish the alignment process' search space. Xue et al. [47] regarded ontology matching as a prediction problem, with the objective of combining a variety of interest group similarity measures to approximate true matching scores. To increase alignment accuracy and matching effectiveness, neural networks were applied.

Mountasser et al. [35] created a big data interoperability which made use of huge ontologies and randomness logic-based evaluation techniques. The authors also use methods and computing resources in combination with the multicore paradigm (Hadoop/MapReduce) to effectively undertake ontology matching in large-scale data scenarios. Lv and Peng [48] used distributed learning to create an entirely novel model for ontology matching. Customer feedback is more frequently considered throughout this process of continuous improvement, rather than during every new generation. To alleviate user strain, a roulette wheel technique was employed to offer only candidate mappings which are most likely the source of problems. Fallatah et al. [49] showed how a string-based combiner and an instance-based classifier may work together. In the former, template matching is transformed into a two-sided text categorization using ontology class examples, while in the latter, pattern matching trees are combined. This method is indeed not domain-specific and therefore cannot handle diverse and heterogeneous ontologies. Sun et al. [50] used knowledge graphs to complement driven flow graphs, removing the need for prior preprocessing. To minimize the amount of intermediate possibilities, a multilabel weight matrix was used while inspecting a near-optimal matching tree. This allows navigating a flow graph iteratively to accomplish all isomorphic mappings of subgraphs. Portisch et al. [51] laid out the problem of general ontology matching and examined both sources of background knowledge and methods from the literature that ultimately rely on external knowledge.

C. Discussion

The studies in the domain of ontology matching have consistently demonstrated commendable performance when applied to relatively modest datasets characterized by numerous small and medium-sized concepts, as well as in scenarios involving low-dimensional data. This performance excellence is evident in both speed of execution (runtime) and quality of resultant matching outputs. However, a noticeable challenge emerges when these existing solutions are tasked with the alignment of extensive and complex ontological structures, exemplified by large-scale ontologies like S-WoT. In such cases, scalability of conventional methods becomes a bottleneck, leading to sub-optimal matching quality and significantly prolonged runtime durations. In response to this critical limitation, we propose an innovative approach that leverages a synergistic combination of evolutionary algorithms and advanced clustering techniques. This novel framework is specifically engineered to address unique challenges posed by substantial and intricate ontological structures, thereby enabling more efficient and effective ontology matching in scenarios where existing methodologies struggle to deliver satisfactory results. A summary of existing systems is given in Table I.

III. Problem Definition

In S-WoT, ontologies are seen as a revolutionary method of arranging and preserving information that IoT devices of social web ecosystems have exchanged. In general, an ontology

TABLE I
TAXONOMY OF EXISTING SYSTEMS FOR MATCHING ONTOLOGIES WITH THEIR CONSTRAINTS

Class of Models	Models	Limitation
Traditional	Li et al. [52]	Unable to deal with massive data and with a high number of features.
	Shao et al. [53]	
	Rosaci [54]	
Advanced	Belhadi et al. [32]	Use an outdated matching algorithm and require a long runtime for massive data.
	Djenouri et al. [46]	
	Xue et al. [47]	
	Lv and Peng [48]	
	Fallatah et al. [49]	

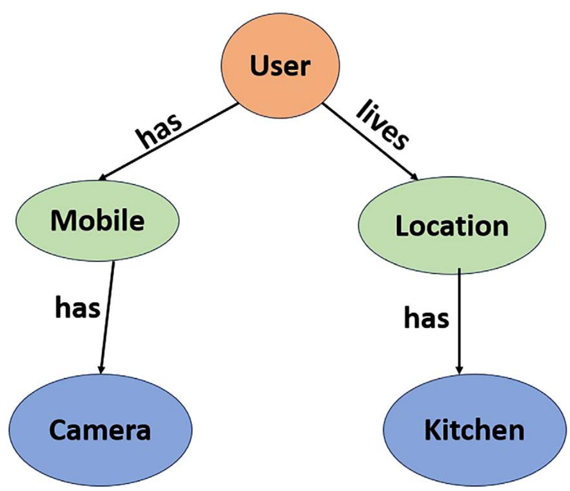

Fig. 1. Illustration of an S-WoT basic ontology. It is made of five concepts {user, mobile, location, camera, kitchen}, with four relations {"has," "lives," "has," "has"}.

defines a domain by breaking it down into concepts and specifying links between them. The "concept" is the most important component of an ontology in connection with the amount of knowledge. Each concept can be defined using a variety of qualities that constitute concrete data. Knowledge may be overtly kept in the shape of data values as instances. Additionally, the majority of ontologies include more information about things like data types or annotations. An ontology is properly defined as a tuple $O = <C, R>$ such that, $C = \{C_1, C_2, \ldots, C_n\}$ is a set of n concepts, and $R = \{R_1, R_2, \ldots, R_m\}$ is the set of relations which connects two different concepts in C.

Fig. 1 displays information on a small portion of S-WoT that is organized according to an ontology. Each of the concepts—user, mobile, camera, and location has specific characteristics. For example, the attributes of the concept "user" include things like username, ID, and job. Four connections exist between concepts as well. As a sketch, the word "has" links the words "user" and "mobiles," indicating that the "user" owns a mobile.

Finding an alignment between two ontologies $\mathcal{O}_1$ and $\mathcal{O}_2$ is the goal of ontology matching. This means trying to figure out concepts of both ontologies that have the same meaning.

IV. ECOM: EVOLUTIONARY CLUSTERING FOR ONTOLOGY MATCHING

In this section, the ECOM method for ontology matching and its components is presented.

A. Principle

The full set of instances for each ontology is divided by ECOM into a number of interconnected clusters. Highly connected instances in every group are then processed based on evolutionary computation. As seen in Fig. 2, ECOM searches for common features among clusters of concepts. The instance set is split into various clusters during the clustering process with an appropriate number of concepts. Concepts in each cluster are highly associated with one another given the vast number of similar features shared by concepts in each cluster. ECOM examines concepts of clusters to identify matching based on evolutionary computation. The alignment process benefits from generated clusters, while mitigating the exploration of all concepts of both ontologies. By developing a novel alignment strategy (instead of comparing two sets of concepts of given ontologies), the alignment step builds on the clustering phase. This accelerates the matching process. By computing their shortest distances, two highly related clusters across ontologies are located using the matching procedure. As a result, each group in the first ontology aligns with a group in the second one that is most similar. In this context, we will explore the evolutionary algorithm to quickly converge to optimal alignments. Algorithm 1 presents pseudocode for ECOM, a framework designed for aligning concepts from two ontologies, denoted as $\mathcal{O}_1$ and $\mathcal{O}_2$, and subsequently producing matching results. The algorithm's workflow involves several distinct steps.

1) Clustering Preparation (Lines 3–4): At the outset, the concepts from both ontologies are clustered. Clustering is executed through two distinct clustering algorithms aimed at efficiently grouping related concepts. The outcome of this phase is the formation of two sets of clusters, denoted as P_1 for concepts from ontology $\mathcal{O}_1$, and P_2 for concepts from ontology $\mathcal{O}_2$.

2) Cluster Matching (Lines 6–15): To establish correspondence between clusters from two ontologies, Algorithm 1 evaluates similarity between each cluster in P_1 and its counterpart in P_2. The cluster from $\mathcal{O}_2$ that most closely resembles each cluster from $\mathcal{O}_1$ is identified and recorded.

3) Cluster Concatenation (Lines 16–24): Algorithm 1 proceeds to match and concatenate identified clusters. This step ensures that related clusters are aligned and combined, forming more comprehensive sets of matching clusters.

4) Final Matching (Line 26): Ultimate matching results are derived, encapsulating aligned and concatenated clusters, signifying successful matching between two ontologies.

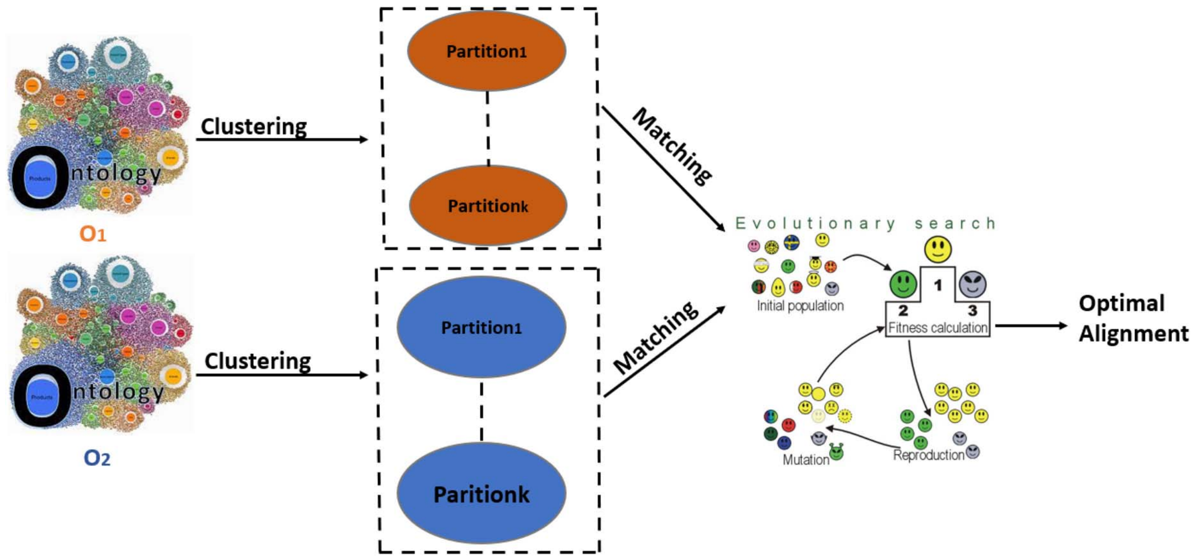

Fig. 2. ECOM framework: the concepts of both ontologies are first decomposed into similar partitions using the clustering method. The set of derived partitions is then explored using an evolutionary process to converge to the best alignments.

Algorithm 1 ECOM Algorithm

Input: $(\mathcal{C}_1, \mathcal{C}_2)$: Sets of concepts of the ontologies $\mathcal{O}_1$, and $\mathcal{O}_2$. IMAX: maximum number of generations.
Output: $\mathcal{A}^*$: Optimal alignment of the two ontologies $\mathcal{O}_1$, and $\mathcal{O}_2$.
$P_1 \leftarrow Clustering(\mathcal{C}_1)$;
$P_2 \leftarrow Clustering(\mathcal{C}_2)$;
$\mathcal{A} \leftarrow \emptyset$;
for i = 1 to $|P_1|$ **do**
  $min_i \leftarrow \infty$;
  $index_i \leftarrow -1$;
  for j = 1 to $|P_2|$ **do**
    $sim_{ij} \leftarrow similarity(p_i^1, p_j^2)$;
    if $sim_{ij} \leq min_i$ **then**
      $min_i \leftarrow sim_{ij}$;
      $index_i \leftarrow j$;
    end if
  end for
  current_generation $\leftarrow$ 1;
  while current_generation $\leq$ IMAX **do**
    generation $\leftarrow$ initialization(p_i^1, $p_{index_i}^2$);
    extended_generation $\leftarrow$ crossover(generation);
    $extended\_generation \leftarrow extended\_generation \cup mutation(generation)$;
    $generation \leftarrow selection(extended\_generation)$;
    current_generation $\leftarrow$ current_generation + 1;
  end while
  $\mathcal{A} \leftarrow \mathcal{A} \cup \{genetation\}$;
end for
return $\mathcal{A}$.

Next, we provide a detailed exposition of clustering strategies employed in ECOM, as well as an in-depth examination of the framework's matching mechanism.

B. Clustering Step

1) K-bMOM Algorithm: We propose the adaptation of K-means bootstrap Median-of-Means (K-bMOM) K [55] for ontology clustering. The method begins by evenly, independently, and with replacement sampling from original concepts to create a set of blocks from a set of concepts. Afterwards, by tying each concept to its nearest centroid, a partition for each block is calculated. Every block's centroid is updated in accordance with its block partition, and then empirical risk is determined. The center of the median block, which has median empirical risk, is chosen as the current block's center. We consider the risk median, which is the empirical real-valued mean of the K-means loss derived from concepts within every block. Therefore, the bootstrap median-of-means approach is applied. There are multiple iterations of these actions. Instead of getting centroids of the last iteration's median block, centroids corresponding to the most recent iterations are aggregated to produce a more accurate assessment. This approach produces a codebook supplied consensus-based robust clustering using a set of candidates that are calculated on bootstrap subsamples. In contrast to existing consensus clustering that aggregates candidate in a more complicated manner by utilizing some similarity measures between various ways of clustering, we choose one of the candidates using a straightforward median criterion for one-dimension statistics. This is one of the key differences between our approach and that of consensus clustering.

2) $DWMB$ Algorithm: We propose an adaptation of the divide well to merge better (DWMB) algorithm [56] for ontology clustering. It is a nonparametric technique that can discover existing clusters in concepts without concerns about the number of preceding clusters. Similarly to hierarchical clustering, it is based on two paradigms: dividing and merging. This is a significant distinction in the merging technique, in which concepts clustered as subclusters in the division phase are employed. This is also different from traditional bottom-up approaches that are based on each individual concept. Additionally, density-based features of the algorithm are used to determine whether or not to combine two clusters by computing the area where clusters overlap. Calculating the ideal number of concept clusters for each concept size is the first step in the division process. An enhanced K-means algorithm is utilized to help to figure out the correct proportion of subclusters for every concept size. The optimal amount of clusters to use during the division phase is automatically determined with the aid of an optimized version of K-means. The division step is prevented from experiencing issues with over splitting and under splitting concepts by an optimized choice for k. To identify current concept clusters, subclusters are evaluated for fuzing. During this phase, all discovered subclusters from the division phase are fused with nearby subclusters. Only two adjacent subclusters are reviewed for merging at a time, and the procedure terminates when all subclusters have been evaluated. Subclusters are either retained separately as independent clusters or fused together based on evaluation decisions.

C. Matching Process

The knowledge gained from the clustering step will be used in the matching process. The major goal of this stage is to focus on the most important concepts rather than analyzing both ontologies' whole collections of concepts. Suppose that G_1 and G_2 represent the corresponding sets of clusters for two ontologies, $\mathcal{O}_1$ and $\mathcal{O}_2$. Groups G_1 and G_2 are scanned in order to pick similar clusters, and the similarity between each pair of clusters g_i^1 and g_j^2 is determined using

$$\text{distance}(g_i^1, g_j^2) = |g_i^1| + |g_j^2| - |g_i^1 \cap g_j^2| \quad (1)$$

where $|g_i^1|$, $|g_j^2|$, and $|g_i^1 \cap g_j^2|$ represent the number of properties in clusters g_i^1 and g_j^2 and their intersection, respectively. The most similar clusters for both ontologies are selected. Let $S(G_1, G_2)$ be the set of most similar clusters of ontologies $\mathcal{O}_1$ and $\mathcal{O}_2$, respectively. The set of most similar clusters is explored to retrieve the matching between $\mathcal{O}_1$ and $\mathcal{O}_2$. A naive strategy is to examine each pair of concepts of similar clusters to find similar concepts in $\mathcal{O}_1$ and $\mathcal{O}_2$. This requires a large amount of time and enormous resources to make the process efficient for immediate processing.

Our conceptual framework revolves around harnessing the evolutionary process to discern analogous clusters within a given dataset. This approach hinges on a comprehensive solution space, encompassing every conceivable alignment between clusters that exhibit similarities. At the core of our methodology lies the concept of a fitness function, which operates as a measure quantifying the quality of each alignment. Our overarching objective centers on cultivating a population of alignments that collectively garners the highest possible alignment scores. The fundamental premise of our approach involves navigating and exploring pairs of similar clusters within the dataset. To achieve this, we employ a suite of genetic operations tailored for the task, including the following.

1) Population Initialization: This initial phase lays the foundation for the evolutionary exploration by populating the solution space with a diverse set of candidate alignments.

2) Crossover: This genetic operation facilitates the exchange of genetic material (in this context, alignment information) between different pairs of clusters, thus diversifying the pool of potential solutions.

3) Mutation: In this step, we introduce controlled variations into alignments to explore potentially more favorable configurations, promoting adaptability, and innovation within the population.

4) Selection: The selection process involves identifying and retaining alignments with superior alignment scores, thereby emulating the principles of natural selection to propagate promising solutions.

Through these interplay of genetic operations, our approach orchestrates an evolutionary journey to iteratively refine and enhance the alignment of similar clusters, ultimately striving to achieve optimal alignment scores that encapsulate the essence of cluster similarity within the dataset.

D. Discussion of Complexity Reduction Benefits in $ECOM$

Exploring decomposition and evolutionary algorithms to increase the performance of ontology matching in real-time use offers several potential benefits.

1) *Scalability:* Existing ontologies on the Web are too large or complex to be solved in a reasonable amount of time. Dividing them into smaller subontologies can make them more manageable. In addition, exploring the evolutionary algorithm within each subontology can help distribute workload and reduce overall complexity of ontology matching.
2) *Parallelization:* Depending on the nature of the subontologies, it is possible to solve them in parallel, which can lead to significant performance improvements. This is especially true for distributed systems, where each subontology can be assigned to a separate processor or node.
3) *Modularity:* By decomposing an ontology into smaller subontologies, each subontology can be approached separately and tested independently. This makes it easier to identify errors or bugs in the matching process and allows the entire development process to be more modular and iterative. In addition, the evolutionary algorithm can be easily run on each subontology rather than on an entire ontology. This helps in the fast convergence of optimal alignment.
4) *Reusability:* If the original ontology is a frequently occurring or recurring ontology, splitting it into smaller subontologies can facilitate reuse of existing ontology matching algorithms. For example, if each subontology can be solved with a known ontology matching algorithm, the overall solution can be composed from a set of existing building blocks, which can reduce the amount of code that needs to be rewritten.

V. Performance Evaluation

The proposed ECOM was validated by extensive simulations. In this study, two datasets that are commonly used in the field of ontology matching are used.

1) *DBpedia*[1]*:* It is part of Wikipedia's hub dataset. This ontology database has 2795 unique data concepts and 4 233 000 occurrences.

[1]http://wiki.dbpedia.org/Datasets

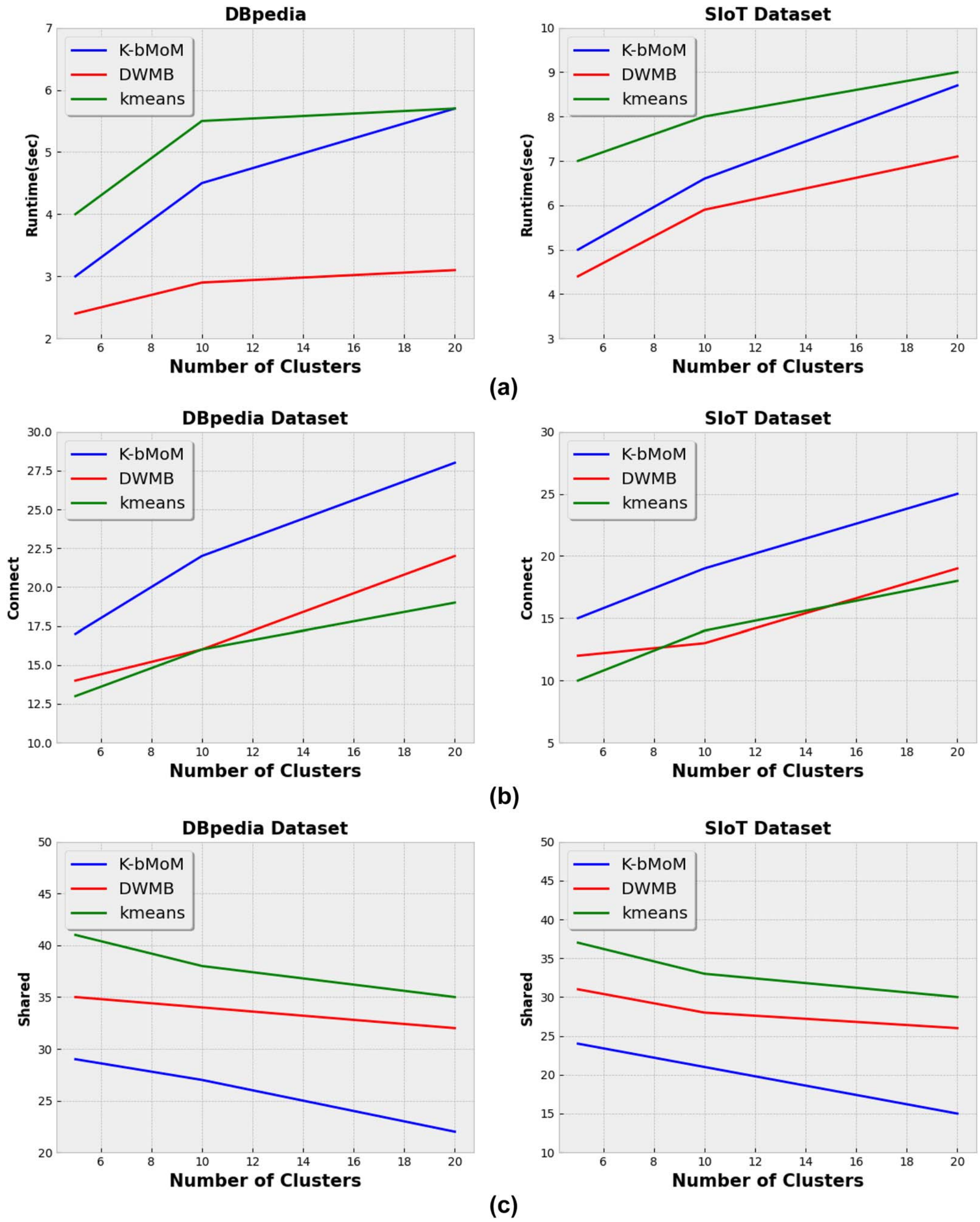

Fig. 3. Performance results of the clustering step. (a) Runtime. (b) Connect metric. (c) Shared value for the dataset mentioned above the sub-figure.

2) *SIoT dataset [57]:* It is designed for modeling SIoT interactions of more than 50 000 users connected through different devices including smartphones, cars, tablets, smart watches, and others.

A. Performance of Clustering Step

Two clustering methods K-bMOM and DWMB with the K-means algorithm are utilized for comparison. This allows validating the proposed adaptation and selecting the best clustering algorithm that will be used in the matching process. We used two different evaluation measures. The primary metric, denoted as “connect” [see (2)], is employed to quantify the intracluster connectivity of conceptual elements. Our objective is to maximize the “connect” metric for each algorithm. This metric uses “sim” [see (3)] that computes the similarity between two different partitions. The secondary metric, termed “shared” [see (4)], serves the purpose of assessing the degree of conceptual overlap among distinct clusters. Our purpose with the latter is to minimize the “shared” value for each algorithm. The following equations describe these measures:

$$\text{connect}(P) = \frac{\sum_{i=1}^{|P|} \text{sim}(P_i)}{|P|} \tag{2}$$

where

$$\text{sim}(P_i) = \frac{\sum_{j=1}^{|P_i|} \text{distance}(e_{ij}, p_i)}{|P_i|}. \tag{3}$$

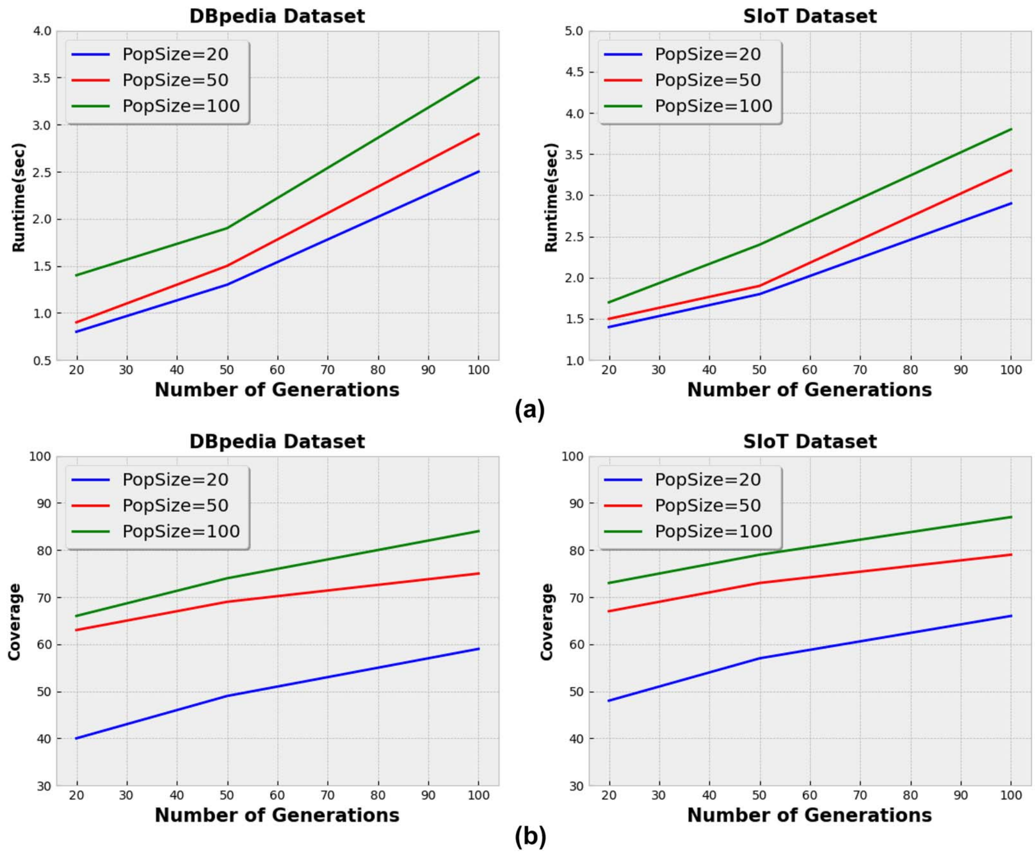

Fig. 4. Results performance of matching step. (a) Runtime. (b) Coverage for the dataset mentioned above the sub-figure.

Note that e_{ij} is the jth element of P_i, p_i is the centroid of the partition P_i, $\text{distance}(e_{ij}, p_i)$ is the distance between e_{ij} and p_i

$$\text{shared}(P) = \text{Max}(\{\text{share}(P_i, P_j) \forall i, j \in [1 \ldots |P|^2]\}) \quad (4)$$

where $\text{share}(P_i, P_j)$ is the number of shared concepts between P_i and P_j.

Fig. 3 shows the metrics "execution time," "connect," and "shared" when varying the number of clusters. The plots show a slight increase for all algorithms, but with slight differences between them in both datasets for runtime processing. The results also show that K-bMOM provides high connectivity between concepts within clusters and a low number of shared concepts between different clusters. For example, the connectivity of K-bMOM exceeds 27 when using 20 clusters for the DBpedia dataset, while the other algorithms (DWMB and K-means) are below 21 for the same configuration. These results demonstrate the applicability of the clustering algorithms developed in this work. We will therefore use K-bMOM with 20 clusters for the remaining experiments.

B. Matching Step Performance

The two matching strategies are utilized for comparison, exact versus evolutionary. The following experiments allow the investigation of these two strategies and select the one that matches better for the use in the whole ECOM pipeline. We used coverage measure that computes the coverage of alignments obtained by the evolutionary based strategy with alignments of the exact strategy. The aim is to minimize the "coverage" value for the evolutionary based strategy by exploring different population size and different generations. The following equation describes the coverage measure:

$$\text{coverage}(A) = \frac{|\text{Alignment}_A|}{|\text{Alignment}_{exact}|} \quad (5)$$

where A is the evolutionary strategy used for a given population size and a given number of generations. Alignment_A and Alignment_{exact} are the sets of alignments retrieved by A and the exact strategy, respectively.

Fig. 4 portrays the performance outcomes obtained from the matching phase, serving as an empirical evaluation of the algorithm's efficacy. Specifically, the following observations can be discerned from the results.

1) *Runtime Behavior:* Fig. 4 illustrates the runtime behavior of the evolutionary strategy, which exhibits a gradual increase in execution time for both datasets under consideration. This temporal trend suggests that as the algorithm progresses, its computational demands grow at a manageable pace.
2) *Matching Coverage Analysis:* The matching step's coverage is meticulously assessed and displayed in Fig. 4. Across all population configurations and datasets, a discernible augmentation in matching coverage is evident. This enhancement in coverage can be attributed to two primary factors: the population size and the number of generations. Collectively, these factors contribute to the variability in coverage, spanning a range from 40% to 90%, as graphically depicted.

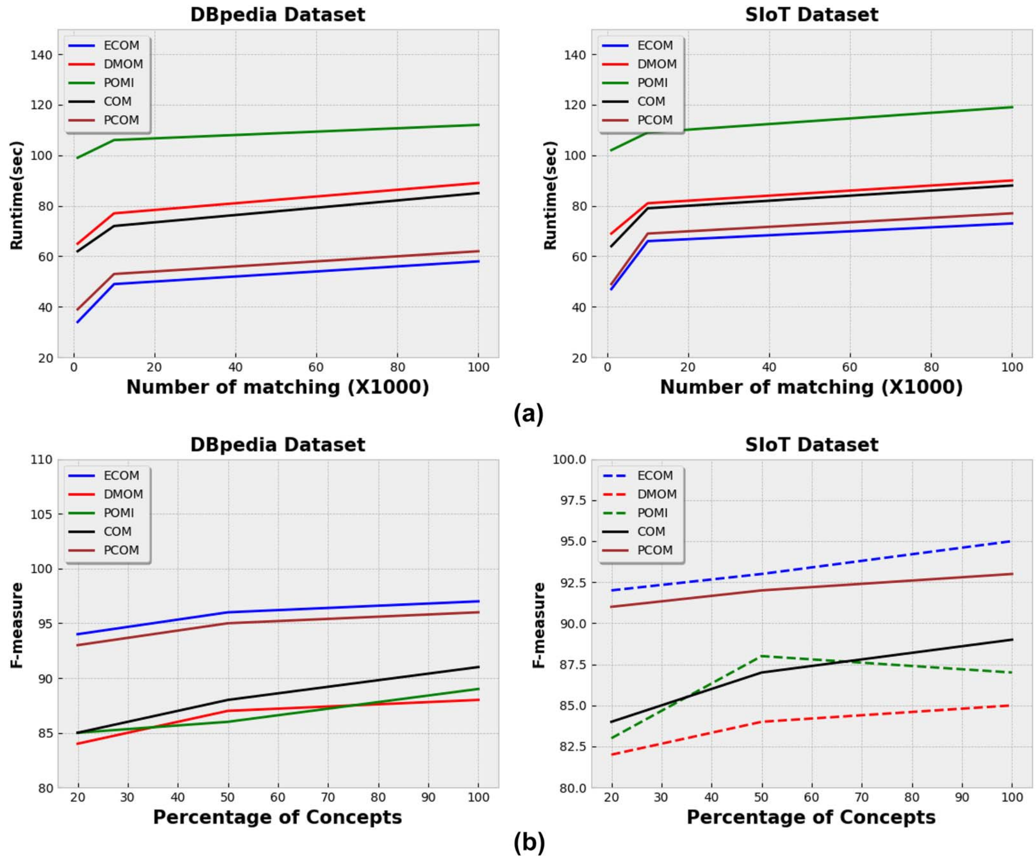

Fig. 5. ECOM versus state-of-the-art algorithms. (a) Runtime. (b) F-measure for the dataset mentioned above the sub-figure.

These empirical findings substantiate the practical applicability of the evolutionary strategy, underscoring its superior scalability in comparison to the exact strategy. As a result, in the subsequent experimental investigations, we will adopt the evolutionary strategy with a specific configuration, employing 100 generations and maintaining a population size of 100 individuals as the chosen settings. This choice is motivated by the promising performance observed in this assessment.

C. ECOM Versus State-of-the-Art Algorithms

The best configuration of ECOM resulting from the previous experiments (in terms of clustering algorithm and the matching strategy) is contrasted to cutting-edge matching algorithms. F-measure is used to assess the ontology matching's quality, which produces the output of the alignment, L, and a reference alignment, L^*, as the result of the ontology matching. This is explained, respectively, as follows:

$$F(L, L^*) = \frac{2 \times P(L, L^*) \times R(L, L^*)}{P(L, L^*) + R(L, L^*)} \tag{6}$$

where precision P is calculated as

$$P(L, L^*) = \frac{|L^* \cap L|}{|L|} \tag{7}$$

and recall R is calculated as

$$R(L, L^*) = \frac{|L^* \cap L|}{|L^*|}. \tag{8}$$

We note that domain experts annotated the ground truth, which is a human process. It is represented by the best alignment. In this analysis, DMOM [32] and POMI [46] were taken into account as potential baseline methods. We also consider two variants of ECOM: namely COM, which examines exact matching and PCOM, which considers the use of particle swarm optimization (PSO) in the matching process. The performance on both DBpedia and S-IoT was performed in the following two steps.

1) *Runtime:* Fig. 5 shows the processing time of ECOM, DMOM, POMI, COM, and PCOM using DBpedia and S-IoT. The results confirm that ECOM performs better than DMOM, POMI, COM and PCOM with a lower runtime, especially for a large number of matches. For example, COM, DMOM, and POMI required more than 80 seconds for 80 000 or 1 00 000 matches for both datasets, while ECOM and PCOM required less than 65 s. This confirms that by using an effective technique to analyze the information provided in each cluster of instances, the proposed approach provides a matching process that considers only closely related examples.
2) *Accuracy:* Fig. 5 also evaluates the accuracy in terms of F-measure of ECOM compared to DMOM, POMI, COM and PCOM. The results show that ECOM and PCOM consistently beat the other two approaches. The results also show that the quality of ECOM and PCOM

TABLE II
TOP SIMILAR CONCEPTS RETRIEVED BY ECOM USING THE SIOT DATASET

Topics	Ontology 1	Ontology 2	Alignment Score
Tourism	Torino City	Italian Town	0.78
	Pizza Food	Popular Meals	0.66
	Museum	Attraction	0.71
	Leonardo da Vinci	Galileo	0.69
	Cheap Hotels	Three stars accommodations	0.86
Sport	NBA	Basketball	0.88
	Tony Parker	Team Player	0.91
	World Event	World Cup	0.70
	World Event	Olympic Game	0.85
	Individual Sport	Athletics	0.88
Politics	War	Military Service	0.81
	Negotiation	Parties	0.64
	Debates	Parliament	0.76
	USA	Russia	0.77
	USA	China	0.75

does not depend on the number of data concepts. As shown, the quality of DMOM, POMI, and COM is limited to 87% and 90%, respectively, while the quality of ECOM and PCOM never falls below 90%. These results were made possible by using clustering and evolutionary algorithms to identify the most relevant ontology concepts.

D. Case Study on S-WoT

We conducted extensive experiments with S-WIoT ontologies to analyze the results of $ECOM$ in real-world scenarios. We created ontologies using concepts from various S-WIoT related texts. Using the Markov clustering algorithm, we were able to identify all concepts for a given topic. Table II shows some relevant concepts of ontology matching. Based on the results, we conclude that ECOM is able to discover similar concepts in both ontologies derived from S-WIoT data. For example, ECOM finds that the *Olympics* is more closely related to global events than the *World Cup*. The *World Cup* is a global event that targets a specific group of people who play a specific sport, while the *Olympics* is a global event that targets everyone who is interested in sports.

VI. CHALLENGES AND PERSPECTIVES

In this section, we dive into a comprehensive exploration of various critical issues and propose potential avenues for future development and refinement of ECOM. Our focus centers on its application in the context of aligning ontologies derived from S-WoT, which presents a unique set of challenges and opportunities. First and foremost, we observed several pertinent issues that merit careful consideration. These encompass issues related to scalability and efficiency of ECOM when applied to large-scale S-WoT datasets. We dive into the intricacies of handling diverse data sources and the need for robust strategies to accommodate evolving ontological structures. Data heterogeneity within S-WoT is also another challenge of ECOM, emphasizing the importance of devising techniques to handle disparate data representations and semantics. Next, we go through a deep exploration of challenges and possible research directions for ECOM.

A. Real-Time Processing

The challenge of ontology matching takes on a heightened level of complexity when applied to S-WoT, particularly in scenarios where real-time data processing is imperative. Successful alignment of ontologies in the context of S-WoT hinges upon several critical considerations. First and foremost, it demands a profound comprehension of the semantic context surrounding social data interconnected across the web. This entails recognizing subsumption relations, where one concept encompasses another and ensuring the formal consistency of these relationships. These factors are paramount in achieving accurate and meaningful ontology alignments within the dynamic realm of S-WoT. Moreover, the process of partitioning S-WoT data into coherent and uniform clusters presents promising directions. It is essential to investigate diverse clustering strategies [58], [59] with evolutionary decisions [60]. These studies open intriguing avenues for exploration, offering potential solutions to the intricacies of data organization within S-WoT. Additionally, as S-WoT datasets can grow substantially in size, there is a compelling need to explore parallel processing solutions. The utilization of graphics processing units (GPUs) [61] is a promising direction. GPU can effectively handle computational demands associated with large-scale ontology datasets, potentially expediting the ontology matching process in the context of S-WoT.

B. Evaluation

The assessment of core ontologies for S-WoT data has been a relatively neglected area within the research landscape. There has been a limited focus on systematically evaluating utility and effectiveness of core ontologies in this context. To foster progress and innovation in semantic matching approaches for S-WoT environments, it is crucial to promote the creation of comprehensive evaluation datasets specifically designed for testing ontology matching solutions. Encouragingly, these datasets could serve as a catalyst for the advancement of approaches that leverage foundational ontologies. By providing a standardized benchmark for assessment, researchers and practitioners would have a common ground for evaluating and refining their semantic matching methods in the context of S-WoT data. One notable gap in the existing literature is the scarcity of publicly available alignments generated by various ontology matching techniques. This limited availability hinders reproducible and comparable results across different approaches. Furthermore, the formats chosen for these alignments often lack compatibility with automated processing, making it challenging to conduct systematic evaluations. In response to these challenges, there is a clear intention to contribute to the field by establishing a benchmarking framework for ontology matching in the S-WoT context. This initiative will involve the creation of evaluation datasets and the definition of specific evaluation metrics to assess the quality of matching results comprehensively.

C. $ECOM$ Applicability

The capacity of current smart cities is being exceeded by urbanization and gentrification, which is increasingly causing environmental deterioration. Semantic analysis of smart city data and related events can be used to maximize the usage of these infrastructures. Making cities and communities ecological is aligned with the United Nations' 11th Sustainable Development Goal, and ECOM has the potential to contribute to its achievement. Energy demand is rising worldwide, which is bad for the environment and detrimental for the lives of individuals. Some potential areas where ECOM can be applied are described as follows.

1) *Urban Planning:* Cities around the world are expanding quickly and their population is expected to reach 2.5 billion by 2050. To balance the competing needs for housing and to manage external shocks, it is crucial to understand urban dynamics [62], [63]. Since the amount and diversity of data from multiple sources in smart cities are expanding, ECOM has an essential function in conceptual modeling of smart cities to enhance urban planning skills.
2) *Smart Manufacturing:* A growing number of sensors are being added to machines that may generate a significant quantity of time series data, which is a step further in the implementation of Industry 4.0. However, it is challenging to detect deficiencies in the production process, for example, when the use of a worn tool leads to the production of defective parts or if a manufacturing procedure is prone to polluting the environment. ECOM can be used to connect and comprehend various factors in production environments [64], [65]. It can also be utilized to connect and comprehend different production-related factors and then convey a variety of industrial production process behaviors, like alarms or sensor failures.
3) *Smart Healthcare:* Healthcare is typically funded by governments in most countries, which requires the provision of decent treatments and services at affordable prices. This can only be achieved through the employment of suitable policies and technologies, particularly among health insurers [66], [67]. Precise information management systems that track clients' healthcare demands in line with their health state can be created with the aid of ECOM.

VII. Conclusion

This article addresses the issue of ontology matching in the scope of S-WoT, and a hybrid evolutionary clustering solution has been proposed. The proposed framework called ECOM aggregates ontologies that are strongly linked from S-WoT data into comparable categories using a number of clustering approaches. The core idea is to group examples of each domain into related groups before matching concepts of similar groups rather than whole concepts of two ontologies. Two clustering algorithms were created for ontology matching. These algorithms initially look into both basic and advanced clustering methods. We also developed an intelligent matching algorithm where best alignments are optimized or idealized through an evolutionary process. Our experimental findings demonstrate that while keeping the same matching quality, ECOM beats cutting-edge ontology matching techniques in terms of computational cost. These outcomes also demonstrate ECOM's ability to manage various data types in S-WoT scenarios. In the near future, we plan to adapt ECOM for matching multiple ontologies instead of just two ontologies. This might be useful to understand the behavior of multiagent systems in the context of S-WoT.

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