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A Dynamic Genetic-Based Context Modeling Approach in Internet of Things Environments

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ABSTRACT

Internet of Things (IoTs) enables entities every day to communicate and collaborate with each other for providing information, data and services to inhabitants and users. IoTs consists of a large number of smart devices that can generate immense amount of data with different types. These sensors raw data needs to be modeled in a certain structure before filtering and processing to provision context information. This process is called context modeling. Context modeling provides definition of how context data are structured and maintained through context aware system. However, employing model for every context type through context aware application is static and is specified by the application developer. The main problem in IoTs is that the structure of context data changes overtime, therefore static modeling cannot be adaptable for modeling these changes. In this paper, a new dynamic approach for context modeling based on genetic algorithm and satisfaction factor is proposed. Firstly, the proposed approach uses genetic algorithm to find the best matching between a set of contexts and a set of available context models. Secondly, it uses a satisfaction factor to calculate the satisfaction degree for each context with each available context model and select the context model with high satisfaction degree as the structure model of this context, dynamically. In addition, flexibility indicator property and context based are defined to measure the performance of the proposed approach. The results of conducted simulations show that the proposed approach achieves higher performance than static approach for context modeling.

Key words: Internet of Things (IoTs); Context Modeling; Genetic Algorithm; Satisfaction Degree; Flexibility Indicator.

1. INTRODUCTION

In recent years, Internet of Things (IoTs) has gained significant attention in computing technologies and industry. IoTs is a term which was firstly coined by kevin Ashton [1] in a presentation in 1999. It represents a world where physical objects are connected to each other through the internet with the minimum human intervention. To meet this challenge, a massive number of sensors are needed to collect raw sensor data then turn it to context information. Then, the collected data needs to be modeled according to meaningful manner through context modeling methods. Subsequently, system platform is required to drive new high level context information using low level context. This system called Context awareness and it was firstly defined by Schilit and Theimer [2] in the year 1994. Context-aware Computing for Internet of Things (IoTs) is an important enabler for pervasive and ubiquitous computing systems in solving heterogeneous data source interoperability problem. Context aware system is used in various frame work such as mobile application and smart homes [3] to provide relevant information and services to end-users.

IoTs is considered as the most interesting recent research in current computing era. IoTs aims to provide easier and better life for humanity. It enables people, physical devices, data and application to connect over the internet to permit controlling remotely and interactive integrated services. IoTs services collect and process raw sensor data frequently and reliably then turn it into operational control information. In addition, IoTs sensors are combined with set of protocols and heterogeneous network using significant amount of technologies. Many researchers have addressed IoTs data types according to different perspectives. For example, authors in [4] categorized context data into eight areas: RFID, address/unique identifiers, descriptive data, positional and environmental data, sensor data, historical data, physics models, and command data. In addition, researchers in [5] classified it as two areas, primary and secondary.

The steps carried out for context awareness consists of four major phases which are context acquisition, Context modeling, context reasoning and context reaction. In context acquisition phase, data is obtained from physical sensors or virtual sensors where multiple sensor networks can be connected together through different technologies and protocols. In Context modeling phase, an interface and behavioral description of the physical environment is provided to deal with contexts and how they are collected and

represented. Moreover, modeling techniques is used to validate contextual information to provide new context information. In context reasoning, high level context data is derived from set of contexts. The last phase, context reaction involves methods (query or subscription) [5] to deliver context to the consumer.

The main problem in IoTs is that the structure of context data changes overtime, therefore static modeling cannot adaptable for modeling these changes. In this paper, a new dynamic approach for context modeling based on genetic algorithm and satisfaction factor is proposed. The main goal of the proposed approach is to make the application or middleware system point out the adaptive model for different context types based on optimal selection computing algorithm.

This paper is organized as follows: Section 2 introduces some of relevant research done using context modeling and representation techniques. Section 3 explains and formulates the context modeling problem in IoTs. Section 4 introduces the proposed context modeling approach. Section 5 simulates the proposed context modeling approach and compares it with some of current approaches for different context types. Finally, section 6 concludes the paper.

2. RELATED WORK

IoTs applications for different environment generate large amount of operational data during their execution. The provided data is translated to meaningful context and minimizes their number through context aware middleware architecture. And every context middleware is designed based on specific environment to solve a certain problem [6]. Context modeling is an essential step in context aware computing system which be well-designed context modeling facilitates system structure and it includes design, analysis and representing contextual information [5]. In literature, several context modeling approaches are introduced [5,7]. Perera et al. [5] surveyed the six most popular context modeling techniques and compared them based on some of ubiquitous computing such as interoperability, partial validation and applicability.

Much research demonstrated various context aware pervasive computing system in smart environments [8] and embedded interactions [9]. For smart environment, smart cities realization is usually require connection between heterogeneous smart appliance, communication devices and software services to provide intelligent services to end users. For example, smart living room [10] in which the authors built the system based on ontology model. Also, healthcare environment is presented in [11] to provide healthcare service in which the authors modeled the context information using ontology model. Ontologies is the most expressive and it is often used to represent human daily life situation as a type of data structures using semantic technologies to store update and access contextual information. Modeling approaches under area of ubiquitous computing are divided according to the using of data structure [5]. In spite of complexity of ontology in context representation and information retrieval, ontology mechanism is preferred in managing and representing context especially in real human situation systems. For embedded interactions, embedded smart devices are used in smart environment including cameras, smart phones, sensors, etc. to exchange information using wireless communication technology.

On the other hand, IoTs services consider set of factors such as spatial and temporal constraints [12], energy efficiency [13], configurability, security and communication capacity [14]. Spatiotemporal extent is used in many applications for smart environment. As in [15], authors proposed a preliminary formal spatiotemporal context modeling based on first order logic. In the system, simple context is described by logic model then complicated context is represented using Boolean operator to generate high level context. The system is simple in which it designed only for time and location for every element. But logic model has no standard and contextual information may suffer from incompleteness and ambiguity.

Context representation is a fundamental step to structure the data in which it enables the contextual data to be stored updated and accessed. The context modeling approaches are classified based on data structure used into six techniques [5]. This research proposed new context modeling approach and compared it with the most popular modeling techniques used which are ontology, logic-based, object-based. Ontology based model provides information about the relationship between objects using semantic technologies [16] such as, RDF and OWL languages. It stores the data in appropriate data source according to the ontology structure. It has strong data validation and it allows knowledge sharing between people and software agents so, it does not depend on applications and it allows knowledge integration on different applications. Based on the previous surveys, ontology model is preferred in context representation for context aware system. However, ontology provides expressive context representation, information retrieval is complex because it requires complex query language and context representation is also complex.

Logic based model represents context information based facts, prediction and rules. It can derive high level context using low level context based on constrains and preferences. It supports logical reasoning and any user can add logic to system in the run time. Main drawbacks of logic based model are lack of standardization and this reduces the reusability and applicability, partial validation is difficult to maintain and it strongly coupled with applications.

Object based model provides hierarchies and relationship modeling. It supports encapsulation and reusability as it integrated well into context aware systems using high level programming language. However, it is hard to use in

retrieving information, it supports data transformation over network as it can be used in run time context modeling and storage mechanism. In addition, validation of object oriented designs is difficult due to the lack of standards and specifications.

The authors in [17] demonstrate Context Modeling Toolkit (CMT) made up of context modeling concepts and offers a rule-based context processing engine. CMT framework provides a seamless transition between programmers and end users even if end users have no programming experience.
The main issues of context modeling are there is no standard for specifying the type of information for representation and there is no standard in choosing model for every context in which every model is tailored for a particular application. The main focus of this paper is mapping between different context types and set of models to accomplish tasks in lesser time.

Some of provided modeling methods are not ideal for dynamic context modeling like ontology. They do not enable users to control system application by defining new data or situation at runtime. In addition, changing the context model needs developer to update system developing statically. Probably, the new situation requires different modeling technique to be compatible with the provided situation data. The proposed approach CGBCMA provides how to match between different contexts and the provided different modeling techniques and how to choose the optimal modeling technique for new raw data.

On the other hand, different contexts represent different situations and every context has various properties. Number of contexts, extracted context properties and number of provided models may affect the system performance. So, three cases are studied to examine the performance of the provided approach which are context based cost, property based cost and model based cost. In these three cases, data is tested based on satisfaction degree, modeling cost, flexible stability based property and flexible stability based context.

3. CONTEXT MODELING PROBLEM (CMP)

In context representation phase for IoTs, the problem is how to determine for each context the best model which will be used to represent it to satisfy its requirements and improve the IoTs services and processes. This problem is called Context Modeling Problem (CMP). In this section, the assumptions and models are introduced then the CMP problem will be formulated.

3.1 System Model and Assumptions

IoTs becomes a new challenge in many of the recent applications. Main drawback of current context modeling for ambient intelligence in IoTs is object dependent model which means most of the current models depend on context object and they cannot fit to represent another context object. Moreover, context modeling is a principle phase in any context aware middleware architecture. Current context models works in static mode in which the system cannot change the representation model for a certain context at the run time. Every model is chosen for a certain context in a specific environment by system programmer. One of the greatest challenges for context modeling is how to find the optimal model for representing certain context in IoTs areas. The main goal of this representation is satisfying all satisfaction requirements of reasoning processes that will be done in this context to designate the optimal model for a certain context based on optimal selection algorithm.

Here, the system model consists of a set of contexts, $C= \{c_1 , c_2 ,..,c_i,... , c_n\}$, where each ci represents a certain context in IoTs as parking data, image data, audio data, traffic data, or weather data respectively. A set of models, $M = \{m_1, m_2 , ..., m_j ,... , m_k\}$, where each m_j represents a certain model as key value, markup schema, graphical, object oriented, logic, or ontology which can be used to model some contexts in IoTs. We assume that each context ci needs number of requirements to be satisfied in context modeling phase and is denoted as $Req(c_i)$ and is defined as follows:

$$\text{Re } q(c_i) = \{ri_1, ri_2, ... ri_l, ... ri_y\} \quad (1)$$

where r_{il} represent a requirement and y is the number of requirements. Here, the satisfaction requirements for a context c_i by a model m_j is denoted as $SReq(c_i, m_j)$. This satisfaction requirements value evaluates context modeling efficacy. $SReq(c_i, m_j)$ is defined as follows:

$$S \text{ Re } q(c_i, m_j) = \{sri_1, sri_2, ... sri_h, ... sri_x\} \quad (2)$$

where r_{ih} represent a satisfied requirement and x is the total number of satisfied requirements. Not that

$$S \text{ Re } q(c_i, m_j) \subseteq \text{ Re } q(c_i) \quad (3)$$

Based on the set of requirements, $Req(c_i)$, and the satisfaction requirements, $SReq(c_i, m_j)$, the utility function for context modeling which is used to measure the efficiency of modeling the provided contexts and defined as follows.

$$u(c_i, m_j) = w_1 * Sat(c_i, m_j) + w_2 * \frac{1}{\cos t(c_i, m_j)} \quad (4)$$

Where $sat(c_i, m_j)$ represents the satisfaction ratio of a context c_i by a model m_j and is defined as follows:

$$Sat(c_i, m_j) = \frac{|S \text{ Re } q(c_i, m_j)|}{|\text{Re } q(c_i)|} \quad (5)$$

and $cost(c_i, m_j)$ represents the cost of modeling the context c_i by the model m_j and this cost can be calculated in different ways as delay time, storage size, or by other means. Finally, w_1 and w_2 are the weights for satisfaction ratio and cost value, respectively. These weights represent the importance of satisfaction ratio and cost value for a user or a developer. In

addition, the values of w_1 and w_2 must satisfy the following condition:

$$w_1 + w_2 = 1 \quad (6)$$

3.2 Problem Formulation

The system model aimed to maximize the utility function provided that each context is modeled by only one model approach. Based on system models and assumptions, the CMP problem can be formulated as follows.

$$Maximize\ U(C, M) = \sum_{i=1}^{n} \sum_{j=1}^{k} u(c_i, m_j) * x_{ij} \quad (7)$$

such that,

$$x_{ij} \in \{0,1\} \quad , \quad (8)$$

$$\sum_{j:(i,j)} x_{ij} = 1 \quad , \quad (9)$$

$$\sum_{i:(i,j)} x_{ij} \leq |c| \quad , \quad (10)$$

Constraint (8) represents the decision variable x_{ij} , where if x_{ij} is equal to 0, this means that a context c_i is not modeled by a model m_j while if x_{ij} is equal to 1, this means that a context c_i is modeled by a model m_j. Constraint (9) means that each context c_i is modeled by only one model m_j . Constraint (10) means that the number of contexts that are modeled by different models is less then or equals the number of contexts.

Based on this formulation, CMP is an optimization problem and the value of decision variable x_{ij} must be determined to solve this problem. In the next section, the proposed approach will be introduced to solve CMP.

4. THE PROPOSED ADAPTIVE CONTEXT MODELING APPROACH

In this section, to solve the CMP problem that being formulated in the previous section, a new approach called *Dynamic Genetic-Based Context Modeling Approach (DGBCMA)* is proposed.

4.1 Basic Idea

DGBCMA is a heuristic approach to solve the optimization CMP problem for maximizing the context modeling satisfaction and minimizing the modeling cost. To satisfy these goals, the basic idea of DGBCMA is based on 4 issues: (1) determining the set of requirements properties of each context type, (2) determining the set attributes of model, (3) calculating the satisfaction degree of each context type based on its requirements properties, and (4) selecting the most appropriate model for each context by using genetic algorithm which will maximize the satisfaction degree of the context and minimize its modeling cost.

4.2 Proposed approach

Based on the basic idea of DGBCMA, the proposed approach consists of four phases: (1) Determination phase, (2) Calculating phase, (3) Selection phase, and (4) Matching phase. These phases are described as follows.

A. Determination phase

In this phase, DGBCMA determines for each context type ci all its related requirements which are represented as a set of required attributes $RC_i = \{rc_{i1}, rc_{i2}, \ldots. rc_{in}\}$. In addition, the DGBCMA determines for each context model m_j all of its related properties which are represented as a set of attributes $AM_j = \{ar_{j1}, ar_{j2}, \ldots. ar_{jk}\}$. This set of attributes represents the properties that can be satisfied by model m_j.

B. Calculating phase

In this phase, DGBCMA calculates the satisfaction degree of each context c_i with respect to each model m_j by using equation (5). Also, DGBCMA calculates the modeling cost of each context c_i to be modeled by a model m_j. Finally DGBCMA calculates the utility function $u(c_i, m_j)$ by using equation (4).

C. Selection phase

In this phase, to select the most appropriate model for each context, DGBCMA uses a genetic algorithm to find the value of a decision variable x_{ij}. Here, a genetic algorithm creates a selection scale based on an evaluation criterion for each pair of context type and context model (c_i , m_j) by using the calculated utility function in the previous step.

D. Matching phase

In this phase, fitness degree is used from the previous phase based on specified requirements to match each context type with a compatible model for representation.

Algorithm 1*:* DGBCMA algorithm to represent context with a compatible model works as follow:

Input:

1) $C=\{c_1,c_2,\ldots.c_n\}$is a set of all available contexts.
2) $M=\{m_1,m_2,\ldots\ldots m_k\}$ is a set of all available models.
3) $RC_i=\{rc_1,rc_2,\ldots rc_n\}$is a set of required context attributes.
4) $AM_j= \{arm_1,arm_2\ldots\ldots arm_k\}$

Process:

1) Calculate the $Sat(c_i, m_j)$ by Equ:(5).
2) Calculate $u(c_i, m_j)$ by equ.(4).
3) Calculate x_{ij} by genetic algorithm.
4) Calculate U(C, M) by equ.(7).
5) Match each context with a compatible model by Max $U(C_i,m_j)$.

5. SIMULATION AND RESULTS

This section evaluates the performance of the proposed schema DCMT which maps every context data type to only one model of modeling techniques.

5.1 Simulation setting

To show the performance of DGBCMA for different contexts, we conducted a model system based on twenty contexts for different environment with six context models. The set of simulated contexts are parking, audio, images, weather, road traffic audio and mobile data. Subsequently, satisfaction requirements for contexts and models are extracted according to parametric evaluation matrix [7] where context requirement for every model is subset of context requirements. The utility function $u(c_i, m_j)$ for every context and model is calculated by using equation (4). Here, the utility function $u(c_i, \underline{m_j})$ is considered as a fitness function of genetic algorithm.. The objective of genetic algorithm is to select the optimal model for every context based on maximizing fitness function such that each context is represented by only one model. All simulation experiments are conducted by using MATLAB.

5.2 Performance Matrices

To measure modeling approach system effectiveness, two flexibility indicators are defined based on the number of context properties and the number of contexts. These flexibility indicators are called *Property-based Flexible Stability* and *Context-based Flexible Stability* indicators. The set of symbols that are used to define the two proposed flexibility indicators and their meaning are shown in table (1).

Table 1: Terminologies (parameters and its description)

parameters and its description	
n_i	is the number of total contexts at step j.
m_j	is the number of assigned contexts for certain models at step j.
x_{ij}	is the number of properties of context i at step j.
avX_i	is the average number of properties for all contexts at step j.
avX_j	is the average number of properties for all assigned contexts for certain models at step j.
FS_{PB}	is the Property-based Flexible Stability.
FI_{CB}	is the Context-based Flexible Stability.

The two proposed flexibility indicators are defined as follows:

A. Property-based Flexible Stability Indicator FS_{PB}:

FS_{PB} measures the effect of the changing number of properties on the modeling approach flexibility. FS_{PB} is calculated as follows.

- Assume that the average number of properties for all contexts at step j is denoted as avX_j and is given by the following equation:

$$avX_j = \frac{\sum_{i=1}^{n_j} x_{ij}}{n_j} \quad (11)$$

- Assume that the average number of properties for all assigned contexts for certain models at step j is denoted as avY_j and is given by the following equation:

$$avY_j = \frac{\sum_{i=1}^{m_j} x_{ij}}{m_j} \quad (12)$$

Here, the property-based flexible stability FS_{PB} is defined as the ratio between the value of changing in average number of properties for all assigned contexts at cascading steps, j and j+1 to the value of changing in average number of properties for all contexts at cascading steps, j and j + 1. So, FS_{PB} is defined as follows.

$$FS_{PB} = \frac{avY_{j+1} - avY_j}{avX_{j+1} - avX_j} \quad (13)$$

Based on the value of FS_{PB}, there are two cases:

- *Case 1*: FS_{PB} >=0, this means that the molding approach is property-based flexible.
- *Case 2*: FS_{PB} < 0, this means that the molding approach is not property-based flexible

B. Context-based Flexible Stability Indicator FS_{CB}:

FS_{CB} measures the effect of the changing number of contexts on the modeling approach flexibility.

Here, FS_{CB} is defined as the ratio between the value of changing in average number of assigned contexts at cascading steps, j and j+1 to the value of changing in average number of all contexts at cascading steps, j and j+1. FS_{CB} is defined as follows.

$$FS_{CB} = \frac{m_{j+1} - m_j}{n_{j+1} - n_j} \quad (14)$$

Based on the value of FS_{CB}, there are two cases:

- *Case 1*: FS_{CB} >=0, this means that the molding approach is context-based flexible.
- *Case 2*: FS_{CB} < 0, this means that the molding approach is not context-based flexible

In addition to these flexibility indicators, a satisfaction degree and modeling cost, which are defined in section 3.1, are used in the evaluation.

5.3 Results and Discussion

Here, the results of conducted simulations of the proposed approach DGBCMA will be introduced and discussed. The conducted simulations are based on three changing parameters: (1) changing the number of context properties, (2) changing the number of contexts and (3) changing the number of models. In every change the data is tested based on satisfaction degree, context modeling cost, FS_{PB} and FS_{CB}. In

addition, in every change, there are two cases of cost will be considered: (a) Context-based cost, which considers only the cost of number of contexts and (b) Property-Context-based cost, which considers the cost of number of contexts and the cost of number of properties of each context. The performance of DGBCMA is compared to ontology, object based and logic modeling approaches. Every experiment is run for five times then the average result is taken for analysis.

5.3.1 Changing number of context properties

In this section number of properties is ranged from 2 to 80 with constant number of models which is 5 and constant number of contexts which is 20. The simulation results will be presented for Context-Based Cost and Property-Context-Based Cost cases as follows:

A. Context-Based Cost

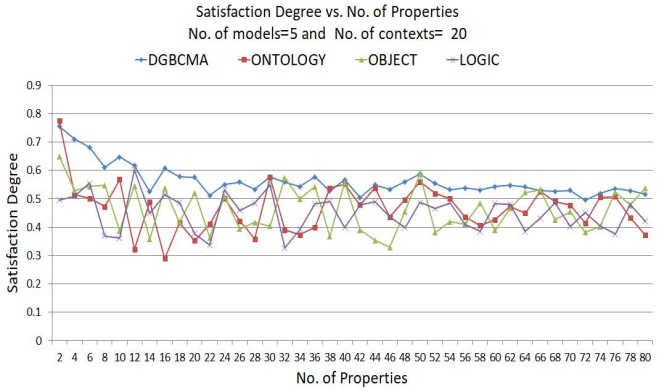

Figure 1: Satisfaction degree based on context cost with changing number of properties.

Figure 1 shows the satisfaction degree against different number of properties. As shown in Figure 1, the satisfaction degree of DGBCMA is larger than ontology, object and logic models. This is because; DGBCMA can dynamically adapt its selection based on the requirements of each context while other models do not.

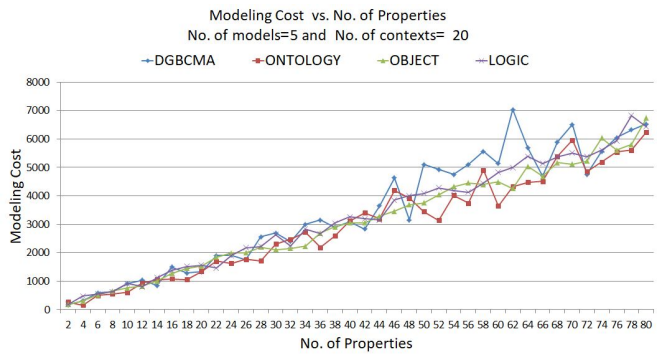

Figure 2: Modeling cost based on context cost with changing number of properties.

Figure 2 shows the modeling cost against different number of properties. As shown in Figure 2, the modeling cost increases as number of context properties increases. This is because when the number of properties increases, an additional cost is needed to model these new properties. It is clear that the modeling cost is almost started with 150 and it climbed gradually with increasing the number of properties while ontology model achieved lower cost comparing to the other three models. The modeling cost of DGBCMA is slightly larger than ontology, object and logic models.

Figure 3 shows the property-based flexible stability indicator, FS_{PB}, against different number of properties based on context cost. As shown in Figure 3, the FS_{PB} value of DGBCMA was started with 0 when the number of properties was equal 2 then it varied between 0 and 1 with different number of properties along the experiment while the FS_{PB} values for ontology, object and logic models were unstable and they ranged between -10 and 5. As a result, DGBCMA has a higher flexibility with respect to different number of properties. This means that DGBCMA can adapt its matching dynamically in efficient way better than other modeling approaches.

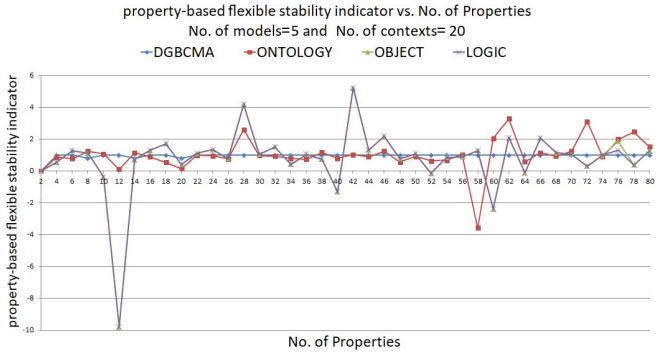

Figure 3: Flexible stability for property based on context cost with changing number of properties.

B. Property-Context-Based Cost

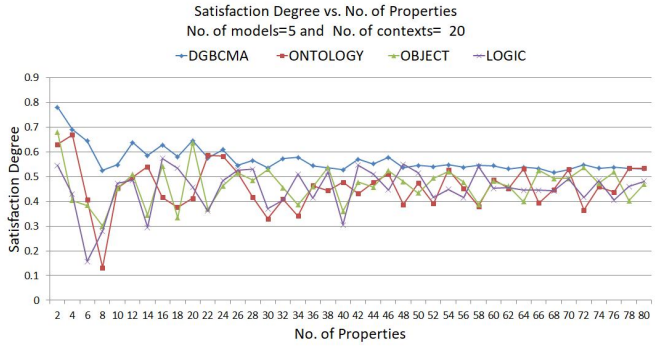

Figure 4: Satisfaction degree based on property and context costs with changing number of properties.

Figure 4 shows the satisfaction degree against different number of properties. As shown in Figure 4, the satisfaction degree of DGBCMA is larger than ontology, object and logic models. This is because, DGBCMA can dynamically adapt its selection based on the requirements of each context while other model do not.

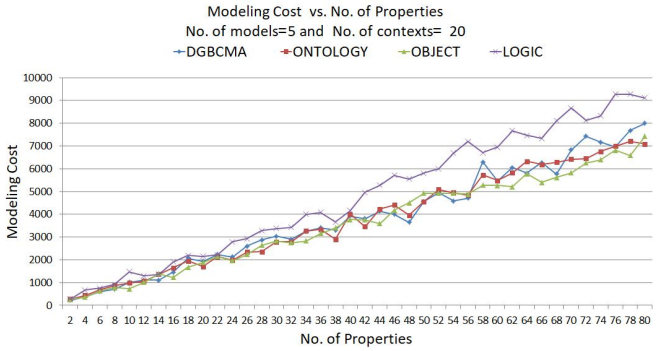

Figure 5: Modeling cost based property and context costs with changing number of properties.

Figure 5 shows the modeling cost against different number of properties. As shown in Figure 5, the modeling cost increases as number of context properties increases. As mentioned in Figure 2 description, more properties require additional cost, this means, modeling cost is proportional to the number of properties. It is clear that the modeling costs are almost started with 150 and they climbed gradually with increasing the number of properties while logic model achieved higher cost comparing to the other three models. The modeling costs of object, ontology and DGBCMA are convergent however object model cost is slightly lower.

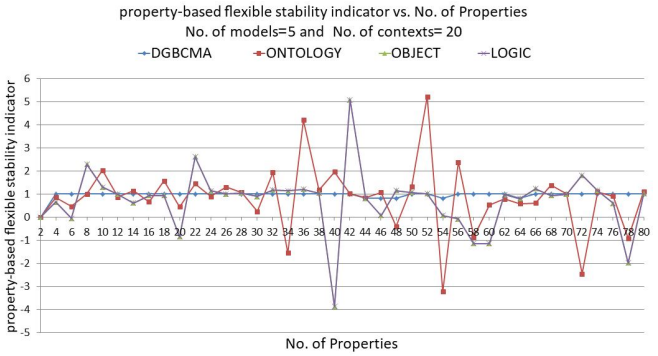

Figure 6: Flexible stability for property based on context and property costs with changing number of properties.

Figure 6 demonstrates the property-based flexible stability indicator, FS_{PB}, against different number of properties based on context and property costs. As shown in Figure 6, the FS_{PB} value of DGBCMA was started with 0 when the number of properties was equal 2 then its rate was almost steady by 1 with different number of properties along the experiment. In addition, the FS_{PB} values for ontology, object and logic models were unstable and their results were increased and slumped dramatically with changing number of properties where they ranged between -4 and 5 along the experiment. As a result, DGBCMA has a higher flexibility with respect to different number of properties. This means that DGBCMA can adapt its matching dynamically in efficient way better than other modeling approaches.

5.3.2 Changing Number of Contexts

In this section number of contexts is ranged from 3 to 41 with constant number of properties which is 20 and constant number of models which is 5. The simulation results will be presented for Context-Based Cost and Property-Context-Based Cost cases as follows:

A. Context-Based Cost

Figure 7 shows the satisfaction degree against different number of contexts. As shown in Figure 7, the satisfaction degree of DGBCMA is ranged between 0.3 and 0.65 approximately and it achieved higher degree than ontology, object and logic models. This is because, DGBCMA can dynamically adapt its selection based on the requirements of each context while other model do not.

Figure 8 shows the modeling cost against different number of contexts. As is presented in Figure 8, the modeling cost increases as number of contexts increases. This is because when the number of contexts increases, an additional cost is needed to model these new contexts. It is clear that the modeling cost is almost started with 150 and it climbed gradually with increasing the number of contexts while DGBCMA approach achieved lower cost comparing to the other three models. The modeling cost of logic model is slightly higher than ontology, object models and DGBCMA.

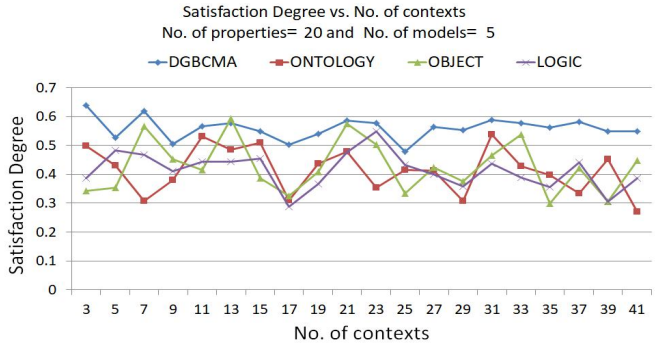

Figure 7: Satisfaction degree based context cost with changing number of contexts.

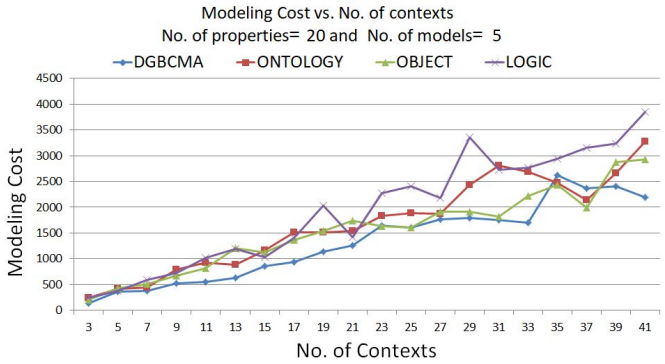

Figure 8: Modeling cost for context based context cost with changing number of contexts.

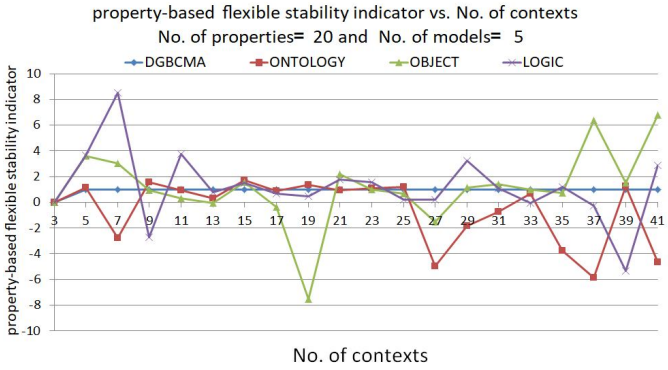

Figure 9: Flexible stability for property based on context cost with changing number of contexts.

Figure 9 shows the property-based flexible stability indicator, FS_{PB}, against different number of contexts based on context cost. As shown in Figure 9, the FS_{PB} value of DGBCMA was started by 0 when the number of contexts was equal 3 and became stabilized at 1 with increasing number of contexts along the experiment while the FS_{PB} values for ontology, object and logic models were unstable and they ranged between -8 and 8, approximately. As can be seen, ontology, object based and logic models are flexible but unstable where the FS_{PB} for these three models climbed and dropped sharply with increasing number of contexts while the FS_{PB} for the proposed approach DGBCMA achieved higher flexibility and stability. This means that DGBCMA can adapt its matching dynamically in efficient way better than other modeling approaches.

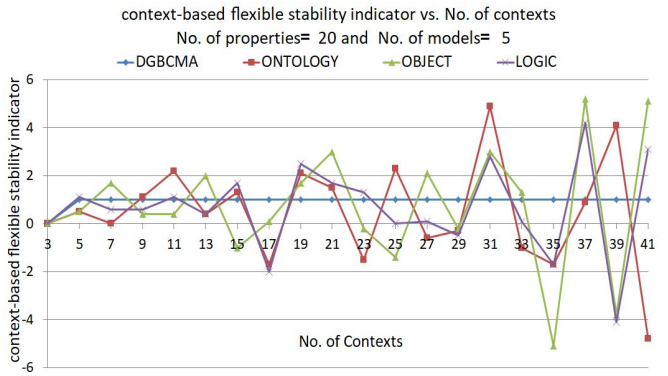

Figure 10: Flexible stability for context based on context cost with changing number of contexts.

Figure 10 shows the context-based flexible stability indicator, FS_{CB}, against different number of contexts. As shown in Figure 10, the FS_{CB} value of DGBCMA was started with 0 when the number of contexts was equal 2 then it became stabilized at 1 with different number of contexts along the experiment while the FS_{CB} values for ontology, object and logic models were unstable and they ranged between -5 and 5, approximately, and they were climbed and dropped dramatically with increasing number of contexts. As a result, DGBCMA has a higher flexibility with respect to different number of contexts. This means that DGBCMA achieves the optimum matching dynamically better than other modeling approaches.

B. Property-Context-Based Cost

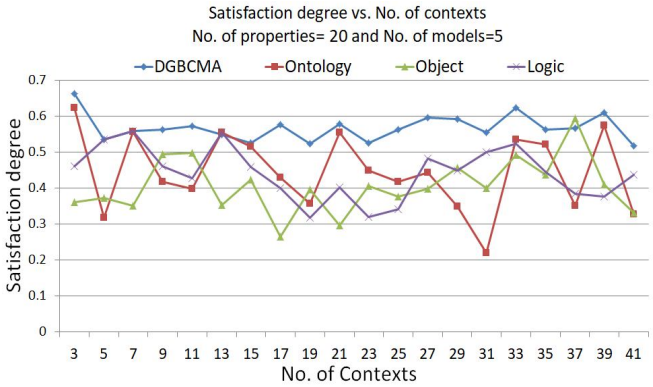

Figure 11: Satisfaction degree based context and property costs with changing number of contexts.

Figure 11 shows the satisfaction degree against different number of contexts. As shown in Figure 11, the satisfaction degree of DGBCMA achieved the optimum degree with changing number of contexts where it is larger than ontology, object and logic models. This is because, DGBCMA can dynamically adapt its selection based on the requirements of each context while other model do not.

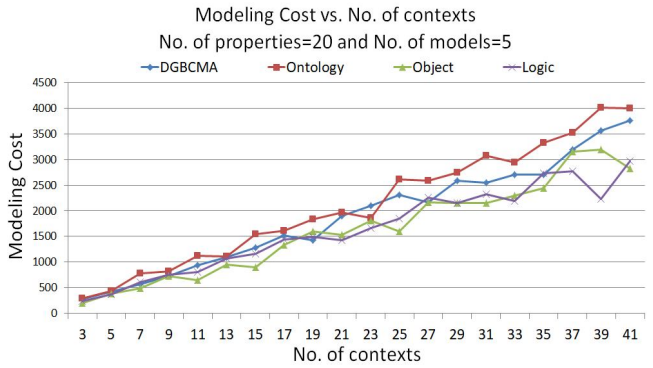

Figure 12: Modeling cost for context based on context and property costs with changing number of contexts.

Figure 12 demonstrates the modeling cost against different number of contexts. As shown in Figure 12, modeling cost is proportional to the number of contexts. It is clear that the modeling cost is almost started with 150 and it climbed gradually with increasing the number of contexts while object model achieved lower cost comparing to the other three models. The modeling cost of DGBCMA is slightly larger than object and logic models while ontology achieved the largest cost.

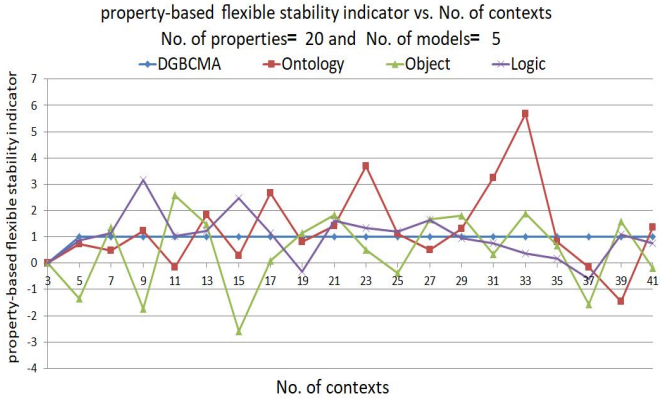

Figure 13: Flexible stability for property based on Context \& property costs with changing number of contexts.

Figure 13 shows the property-based flexible stability indicator, FS_{PB}, against different number of contexts based on property and context costs. As shown in Figure 13, the FS_{PB} value of DGBCMA was started with 0 when the number of contexts was equal 3 then it rose to 1 and became stable with increasing number of contexts along the experiment. On the other hand, the FS_{PB} values for ontology, object and logic models were changed up and down with increasing number of contexts and they ranged between -3 and 6, approximately. As a result, DGBCMA has a higher flexibility with respect to different number of contexts. This means that DGBCMA can adapt its matching dynamically in efficient way better than other modeling approaches.

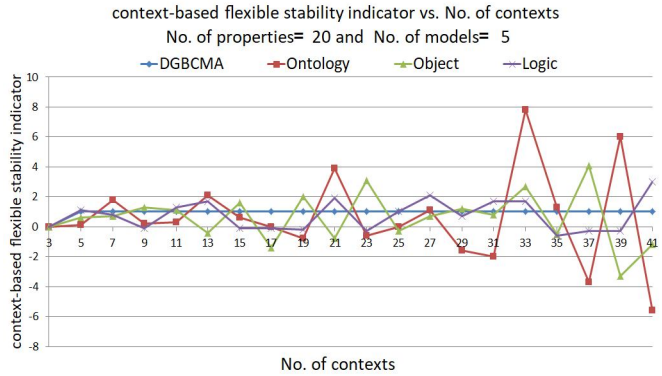

Figure 14: Flexible stability for context based on context and property costs with changing number of contexts.

Figure 14 shows the context-based flexible stability indicator, FS_{CB}, against different number of contexts. As shown in Figure 14, the FS_{CB} value of DGBCMA was started with 0 when the number of contexts was equal 3 then it varied to 1 with different number of context along the experiment while the FS_{CB} values for ontology, object and logic models were unstable and they ranged between -4 and 8. As a result, DGBCMA has a higher flexibility with respect to different number of contexts. This means that DGBCMA can adapt its matching dynamically in efficient way better than other modeling approaches.

5.3.3 Changing Number of Models

In this section number of models is ranged from 3 to 21 with constant number of properties which is 20 and constant number of contexts which is 20. The simulation results will be presented for Context-Based Cost and Property -Context-Based Cost cases as follows:

A. Context-Based Cost

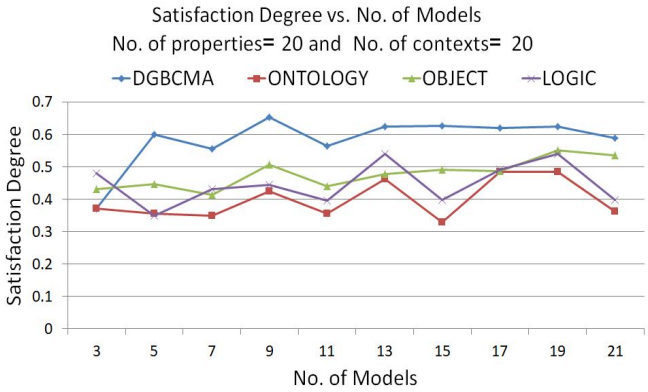

Figure 15: Satisfaction degree for context based on context cost with changing number of models.

Figure 15 shows the satisfaction degree against different number of models. As presented in Figure 15, the satisfaction degree of DGBCMA is larger than ontology, object and logic models. This is because, DGBCMA can dynamically adapt its selection based on the requirements of each context while other model do not.

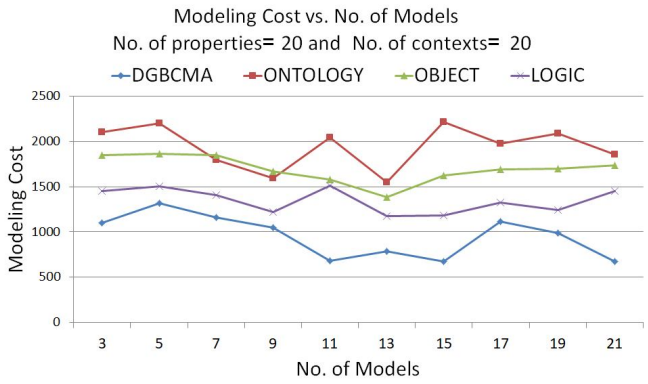

Figure 16: Modeling cost for context based context cost with changing number of models.

Figure 16 shows the modeling cost against different number of models. As shown in Figure 16, the modeling cost increases as number of models increases. This is because when the number of models increases, an additional cost is needed to model these new models. It is clear that the modeling cost is climbed gradually with increasing the number of models while the modeling cost for DGBCMA is much lower comparing to the other three models. The modeling cost of ontology model achieved the largest cost.

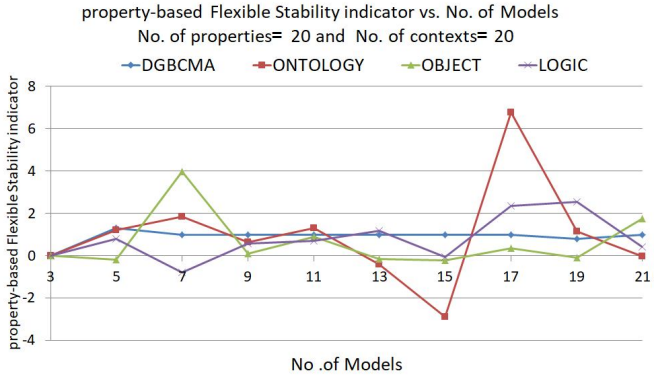

Figure 17: Flexible stability for property based on context cost with changing number of models.

Figure 17 demonstrates the property-based flexible stability indicator, FS_{PB}, against different number of models based on context cost. As shown in Figure 17, the FS_{PB} value of DGBCMA was started with 0 when the number of models was equal 3 then it varied between 0 and 1 with different number of models along the experiment while the FS_{PB} values for ontology, object and logic models were unstable and they ranged between -3 and 7. As a result, DGBCMA has a higher flexibility with respect to different number of models. This means that DGBCMA can adapt its matching dynamically in efficient way better than other modeling approaches.

B. Property-Context-Based Cost

Figure 18 shows the satisfaction degree against different number of models. As presented in Figure 18, the satisfaction degree of DGBCMA is much higher than ontology, object and logic models. This is because, DGBCMA can dynamically adapt its selection based on the requirements of each context while other model do not.

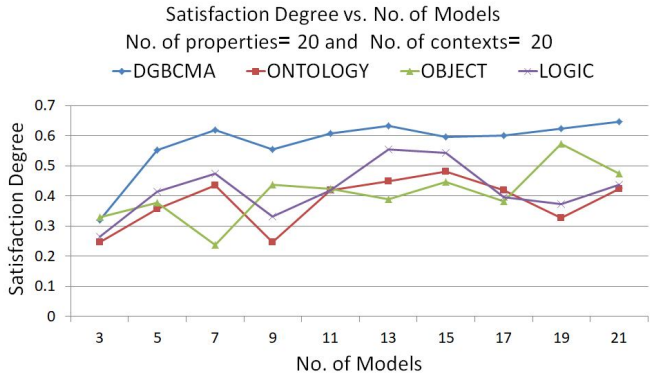

Figure 18: Satisfaction degree based on context and property costs with changing number of models.

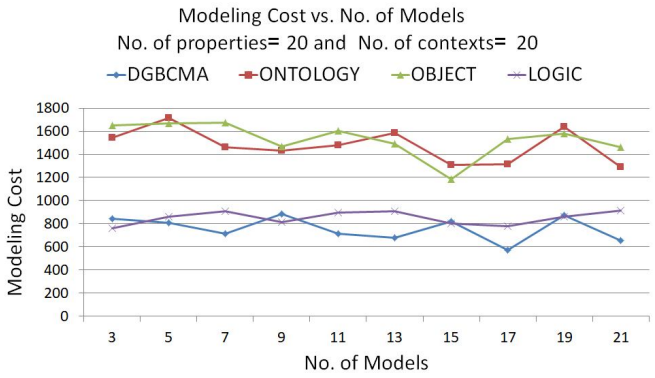

Figure 19: Modeling cost based on context and property costs with changing number of models.

Figure 19 shows the modeling cost against different number of models. As shown in Figure 19, more models require additional cost. It is clear that the modeling cost is climbed gradually with increasing the number of models while DGBCMA approach achieved optimal cost comparing to the other three models. The modeling cost of object model is the largest with increasing models number.

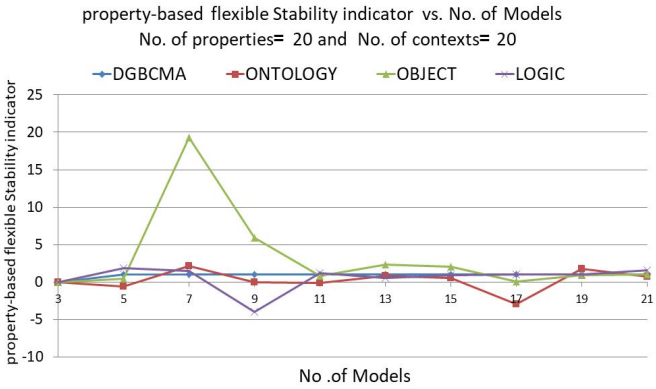

Figure 20: Flexible stability for property based on context and property costs with changing number of models.

Figure 20 demonstrates the property-based flexible stability indicator, FS_{PB}, against different number of models based on property and context costs. As shown in Figure 19, the FS_{PB} value of DGBCMA was started with 0 when the number of models was equal 3 then it varied to 1 with increasing number of models along the experiment while the FS_{PB} values for ontology, object and logic models were unstable and they ranged between -4 and 20. As a result, DGBCMA has a higher flexibility with respect to different number of models. This means that DGBCMA can adapt its matching dynamically in efficient way better than other modeling approaches.

6. CONCLUSION

In this paper, a context modeling problem for Ambient Intelligence in IoTs is described and introduced. To solve this problem, a new dynamic approach is proposed called Dynamic Genetic-Based Context Modeling Approach,

DGBCMA. The objectives of DGBCMA system are maximizing the modeling satisfaction and minimizing the modeling cost by selecting the optimal model for each context dynamically. Genetic algorithm is utilized as optimization method to select model for a certain context based. In addition, two flexibility indicators are defined to evaluate DGBCMA which are called property-based and context-based flexible stability indicators. Different simulation scenarios are conducted based on different metrics, different number of context properties, different number of contexts, and different number of models. The simulation results have shown that DGBCMA is more efficient, more adaptable and more flexible than other existing approaches. In future work, the proposed approach DGBCMA will be used in context reasoning techniques. In addition, a new framework will be implemented based on the proposed DGBCMA.

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