Context Selection Optimization Using Quality of Context for Context Refinement in Internet of Things

Ntalasha Derrick, Li Renfa, and Wang Yongheng

***Abstract*—Context awareness plays a critical role in the Internet of things (IoT) paradigm in providing services appropriate to persons and devices through context information gathering, adaptation and distribution. In this paradigm, context is generated by billions of sensors spreading over a large geographical location. The context generated may not be accurate and appropriate to be used by other context aware applications. Context information is usually not correct because sensor technology used cannot produce error free or accurate sensor data due to various technical and environmental factors. Factors like capability of sensing devices, precision and accuracy of the methods used to collect sensor data, instability of sensors and computing devices, and weather conditions impact the quality of sensor data. To improve the input quality of context refinement process in the middleware framework that deals with context management for intermediating between sensing systems and context aware applications, context selection optimization using Quality of Context is proposed (QoC). This paper provides a methodology that uses QoC in the context refinement process because quality of low level context information is an indicator of whether or not the high level context information makes sense or not. IoT context selection optimization uses Particle Swarm Optimization (PSO) and combined confidence for QoC to select context objects from the IoT domain. This advanced algorithm uses QoC confidence as criteria to search and extract context objects with the highest combined confidence value. The results of the experiments indicate that input context refinement is improved through selecting contexts that are highly reliable.**

***Index Terms*—Context and context awareness, context refinement, quality of context, particle swarm optimization (PSO).**

I. Introduction

For the IoT to fully evolve to its full potential, the computing criterion has to move from the traditional mobile and wireless computing systems to the use of portable devices that connect everyday existing object and incorporate intelligence into the environment. Therefore, the IoT paradigm [1] should acquire, process and convey quality context information [2] to where it is relevant if context aware computing [3], [4] can be accomplished.

As context awareness [5] makes the key component of IoT, collecting and extracting high level context information, and providing this information to the appropriate services and users is necessary. Therefore, the quality of context information must be considered in the context refinement process.

High quality context information plays a critical role in systems adaptability to changing contextual requirements. The higher the quality of this information the more reliable the system is, to situations and in the provision of quality services to users and devices. Therefore, the quality of context information must be conserved so that only high quality context information is used effectively.

Due to the vastness of the IoT domain, the realization of perfect context information is farfetched. Studies by [6] have shown that context information is usually imperfect and uncertain due to sensing technologies that are not explicitly equipped to handle diverse sources of context information. Furthermore, the design of context aware systems is on the premise that of clearly understanding the problems of acquiring reliable context information so that these problems are taken into account in the design and usage of this information. Systems are built and designed to accommodate imperfect context information. Clearly, this way of dealing with imperfect information makes context aware systems to be unreliable and context refinement is a promising avenue.

Without using QoC in the refinement process of context information, context aware computing will not be achieved as context understanding and interpretation will not be fully meaningful, and the vision of IoT machine to machine will not be attained easily. Context refinement has been defined [7] as a process of coming up with concrete context information from imperfect information using context attribute values.

To address the problem of context refinement, QoC was envisioned. With this concept, context acquired is subjected to various context parameters to increase its reliability.

In this paper, we explore how IoT context selection optimization can be achieved by using Particle Swarm Optimization (PSO) and combined confidence for QoC to select context objects with highest combined confidence in its context information. The best context value is selected through the PSO technique. The optimization process takes into account an individual QoC value called the combined confidence value obtained from context information parameters to select the best quality value.

This paper is organized as follows; in Section II, we present related works highlighting the most important recent researches done. In Section III, we discuss confidence for QoC using context weighting, and QoC parameters. In Section IV, we describe Context Refinement, PSO, PSO context selection, Refinement architecture and the algorithm flow chart. In Section V, we discuss experimented results and

Manuscript received January 14, 2016, revised July 16, 2016.
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doi: 10.18178/ijiee.2016.6.4.634

in Section VI, we make our conclusions and future works.

II. RELATED WORK

Many researchers have done some works related to our topic to improve the performance of context aware systems in the IoT paradigm. In this section of our work, we describe the state of art research efforts that give highlights on QoC and its parameters, relevance of quality context information and service selection using QoC.

A QoS aware service selection optimization [8] was proposed that used a matching algorithm to filter candidate web services. The algorithm used Multi-Objective Optimization (MOOP) to select the best service. The MOOP was used to find a solution that maximizes a given utility function using weights. The social context in conjunction with a context filter rule were used in the service lifecycle in discovery, selection and composition candidate services and selecting appropriate service matching user's context. In this work only the required best service would be selected according to the user requirements. Our algorithm uses PSO and QoC to select the context information that is objectively evaluated using context attributes.

The authors of [9] fully addressed the QoC parameters providing formulae on how each context parameter could be calculated. They stressed that QoC gives more worth of context information to a specific application. Each selected QoC parameter was evaluated to suit a collection of subscribed applications along with context information. This enhanced the acquired context information as each application was given information according to its own requirements. Our research goes into detail in using these parameters to generate combined confidence of the context information which the PSO algorithm uses to selects the most reliable information.

Authors in [10] proposed a QoC model that is used to align existing QoC models using it as a reference to an existing standard metrology vocabulary. They defined a vocabulary that fits perfectly to the concepts used by existing QoC models. Despite the terminology alignment, the most important contribution of their QoC model was the explicit differentiation of trustworthiness as a quality attribute of the provider of the context information and not of the context information instances. In our research, trustworthiness is a quality measure that indicates the belief that we have in the correctness of information in a context object. Trust-worthiness of a context object is highly affected by the space resolution, i.e., the distance between the sensor and the entity. The farther away the sensor is from the entity, the more doubt there will be in the correctness of information presented by that context object. Along with the space resolution, accuracy with which the sensor collects context information, also affects the trust-worthiness of the context object.

Their model defined a QoC management architecture that manages the QoC attributes and trustworthiness of context providers in order to help context-aware service providers in the selection of trustworthy context providers. Our work uses trustworthiness as one of the QoC parameters to determine the combined confidence of the context information provided by that context object.

QoC was defined and its importance was clearly given in [2]. The authors explained the relationship QoC has on both Quality of Service (QoS) and Quality of Device (QoD). These three all look at quality but each has its main focus. Every domain has context information, and this information contains the quality attribute which is called Quality of Context (QoC). According to the authors and many researchers, QoC is defined as any information that describes the quality of information that is used as context information. They went further to talk about QoS and QoD. QoS is specific to hardware components and is any information that describes how well a service performs on this hardware. Devices also contain QoD. QoD is any information about a device's technical properties and capabilities. The notion of quality is intertwined in these three aspects and two approaches were introduced; Bottom up and Top down approach. The other two important aspects to our research which they addressed were selection of context providers and adaptation of context refinement. The work of QoC and context refinement underscores the importance and contribution of our work by coming up with the best context information using many objective attributes of quality and optimization to select the context with the highest confidence.

The authors in [11] proposed a novel QoC-aware access control framework for sharing resources in pervasive environments. The QoC framework used the filtering principle to achieve two things. Firstly filtering was used to discard context data whose quality does not comply with minimum QoC requirements as set in the system and secondly, to select applicable policies based not only on current context, but also on the extent to which that context can be considered true. In doing so, the risk of granting access to resources based on incorrect or ambiguous context information was greatly reduced. This was implemented in the Proteus middleware architecture, a middleware that uses QoC-awareness and semantic technologies to evaluate access control policies. This proposal used set minimum requirements to evaluate context information and was more inclined to access control which is just one of the context attributes we used. The collective value of QoC attributes to determine reliability was not addressed unlike our research.

In [12]-[14] frameworks to manage and resolve conflicts in context data in ubiquitous environments were proposed. These frameworks were used to integrate quality of context, evaluate environment situations in relation to context quality while resolving inconsistencies among various contexts.

COSMOS [12] was used to manage all functionalities of a context manager to collect, interpret data and identifying a situation. During the situation identification, processing context information is conducted more often while data gathering is a continuous process.

The quality of context in COSMOS used a single notion QoC operator integrated in various kinds of QoC parameter operators, dedicated to a particular QoC parameter e.g. Uptodateness. In this approach, the framework only catered for a single QoC parameter even though it can be extended to include more new operators. In our approach all the objective QoC parameters were used to come up with one single value that defined the reliability of the continuous data and context information collection.

Information gain based method was used in [15] to select context information necessary for context reasoning. The authors argued that context reasoning methods are used with an assumption that users have on which kinds of low-level contexts are useful for a given high level context reasoning. This knowledge called “context relationship” was used in their work to select context from the environment after building these relationships. They also said that context relationship is not always available in reasoning, making it difficult to define which factors to include during reasoning since it concerns many factors. They stressed that lack of information about context relationship in most reasoning methods was the major reason why developers selected as many as possible low-level contexts for reasoning. In this way even useless context would be included in the reasoning process. Using such contexts would have no or little bearing on the reasoning methods. So this work primarily used context selected from the environment using context relationship to reason about the information without taking into account the quality attribute of context information.

The authors of [16] addressed the issue of context refinement and proposed an architecture to refine context information in pervasive medical systems. They looked at how medical physicians could enhance context information by specifying the quality parameters. This allowed the physicians to include a quality constraint on the service required. Doing this proved to have enhanced the reasoning process. The architecture included several layers for capturing domain characteristics through domain ontology.

The quality constraint ensured that the relevance of context information correlated to the context information that was processed using specific values of each service parameter indicating the preference of the user. Because of the nature of the medical field, they came up with a pervasive healthcare ontology. In their work, refinement of context information considered quality and relevant parameters specified by medical professionals and the particular characteristics of the pervasive medical domain. The quality of context was not explicitly used to refine the context but relied on the domain professionals to specify what constraints constituted quality and relevance. In doing that, quality constraints were not specific and would vary from physician to physician. Our inclusion of the objective QoC parameters on context information in the context refinement process increases both usage and relevance of the context information that is used by applications, devices and users.

Ref [17] proposed QoC measuring methods that included privacy policies. Their methods considered how raw context information might generate inference or derivation processes that could invalidate the measured QoC information. An example was given on how quality aspects would be considered for a physical address that has multiple attributes using GPS coordinates. In their quest to improve evaluation of the measured QoC information, they defined an OWL-DL QoC model and QoC measuring methods. The measuring of QoC process ensures that privacy, security, resolution, completeness and precision are taken into account as the context information is being measured. Another aspect the proposed framework included was the support of QoC at every layer of sensing and processing as it provided the consumers with this enriched information.

The proposed framework included only a few parameters of QoC of context information and did not address how those parameters could collectively enhance reliability of the sensed, collected and processed.

In [18] the author highlighted how context information obtained through sensors is used to adapt to the behavior of appliances. As indicated, most researchers rarely use a multistage processing architecture to process context information to derive new contexts as it is the future of pervasive computing. They proposed processing tree graphs in handling high error rates in context recognition architecture and to manage multi stage context aggregation processes in large scale ubiquitous computing environments. Scaling effects are the direct effect of locality of context and ageing of context within the modular environment. With these graphs, contexts relevance and reliability was achieved. The proposed solution, Genetic Relation of Context (GRC), used a probabilistic multi site crossover method to preserve alleles of genes in loci. Probabilistic multi site crossover (PMSC), for each locus in a child’s genome randomly chooses one of the genes occupying the same locus in the parents’ genomes and inserts it. This method allows very fast and computational inexpensive determination of the degree of relationship of contexts. The result was a direct representation of the ratio of information derived from the parent context. Their proposed solution used the relationship of context information to achieve reliability where as we used context attributes to determine how reliable acquired context is.

III. Confidence for Quality of Context

Combined confidence calculation is critical to our research and is obtained by taking into consideration all aspects that affect context information and is defined as *“the measure of confidence in the measured context information as provided by the context object*.”

Since the IoT environment is dynamic with an ever increasing amount of context information, context information acquisition needs to be standardized. To standardize the collection and measurement of context information, every argument that affects context information was taken in account and used into calculating the combined confidence of the context. The measured and collected context was classified into two aspects; context weighting and QoC value.

Confidence of context has been calculated mainly on specific QoC parameter under consideration such as, usability, updateness, completeness. The importance of the QoC parameter used depended on the application needs. But the IoT environment has more contexts with different usage and importance. So using individual QoC parameter to calculate confidence of the quality of sensor data cannot suffice for IoT application needs. For example, an application that uses a QoC parameter like updateness to select a context object may end up using low values in other parameters. Therefore, to cater for every application needs in the IoT environment, our approach uses combined confidence calculated from all QoC parameters and Context weight. The context weight is used to indicate the importance of the sensed data applicable to other context aware applications. The weighting of the contexts adds an important dimension to the quality parameter by attaching a weight to the sensor data in reference to the expected value. This is gives a true state of the quality of the context object in question.

A. Context Weighting

The context weighting value was determined by rating of closeness for the measured context value in providing discrimination based on the expected value of interest and has a range of [0,1]. As sensor readings are obtained, they are weighted proportionally to the variances for the expected and expected variable values using equation 1;

$$\omega_i = \frac{1}{\delta_i^{\gamma}} \tag{1}$$

where ω is the weight, δ is the variance and γ the mean. In this way less weight is given to the sensor values with less precise measurement compared to the actual and more weight to measurements that are closer to the actual.

The algorithm dynamically assigns weights as sensor readings are acquired. The closer the measured value is to the actual the closer its value is to 1. A zero (0) value is an indicator that the value is invalid and cannot be used to calculate confidence.

B. QoC Value

Our study takes into account all the objective parameters of context because they measure the degree of conformity of the IoT environment as perceived by the measuring device. Let the sensed data value be the context object *CO*. The following parameters were used to calculate the QoC value; *Up-to-Dateness*, *Trust-Worthiness*, *Completeness*, *Significance*, *Precision*, *Certainty*, *Validity*, *Usability*, *Accuracy*, *Access Right and Representation Consistency*. The description and formula for each parameter is given as follows;

Up-To-Dateness is a quality that measures the validity of context information as given by the context object (CO) at a given time.

$$Age(\mathrm{CO}) = \mathrm{t}_{curr} - t_{meas}(\mathrm{CO}) \tag{2}$$

where Age (CO) is the lifetime of that context object, t_{curr}, is the current time and t_{meas}(CO), the measurement time of that context object (CO) uptodateness is given as

$$U(\mathrm{CO}) = \begin{cases} 1 - \dfrac{Age(\mathrm{CO})}{Lifetime(\mathrm{CO})} if Age(\mathrm{CO}) < \mathrm{lifetime(CO)\,otherwiseCO} \end{cases} \tag{3}$$

Trust-Worthiness is a quality parameter that measures the correctness of information in a context object. Trust-worthiness of a context object is highly affected by the space resolution, i.e., the distance between the sensor and the entity. Let the accuracy of the sensor data be δ. The trust-worthiness, T (CO), of context object CO is defined by Equation.

$$T(\mathrm{CO}) = \begin{cases} 1 - \dfrac{d(\mathrm{S},\varepsilon)}{d_{\max}}) * \delta if d(\mathrm{S},\varepsilon) < \mathrm{d}_{\max}\ otherwise 0 \end{cases} \tag{4}$$

where $d(S, E)$ is the distance between the sensor and the entity. $d_{\max}$ is the maximum distance for which we can trust on the observation of this sensor. δ is accuracy of a sensor as measured on the basis of a statistical estimation

Completeness is a quality measure that indicates the quantity of information that is provided by a context object. Completeness is the ratio of the number of attributes available to the total number of attributes. Completeness, C(CO), of context object CO is evaluated by Equation

$$C(\mathrm{CO}) = \frac{\sum_{j=0}^{m} \omega_j(\mathrm{CO})}{\sum_{i=0}^{n} \omega_i(\mathrm{CO})} \tag{5}$$

where m is the number of the attributes of context object CO that have been assigned a value and w_j(CO) represents the weight of the jth attribute of CO that has been assigned a value. Similarly, n is the total number of the attributes of context object CO and w_i(CO) represents the weight of the ith attribute of CO.

Significance is quality measure is the ratio of context information to maximum critical level that type of context information can have and calculated by the equation

$$S(\mathrm{CO}) = \frac{CV(\mathrm{CO})}{CV(\mathrm{CO})_{\max}} \tag{6}$$

where CV (CO) is the critical value of the context object CO and $\mathrm{CV}_{\max}$(CO) is the maximum critical value that can be assigned to a context object of the type that is represented by CO.

Precision is a quality parameter that indicates the exactness by which a context object CO can measure context information and is given by the equation

$$P(\mathrm{CO}) = \frac{P_{curr}}{P_{\max}} * \mathrm{Pr}_{accuracy} \tag{7}$$

where P_{curr} is the current precision, $P_{\max}$ is the maximum precision and $\mathrm{Pr}_{\mathrm{accuracy}}$ is the known exactness.

Certainty is a quality measure parameter that measures reliability of a context object in obtaining context information and is determined by the reply request and response requests. The equation for certainty is given as;

$$Ce(\mathrm{CO}) = \begin{cases} C(\mathrm{CO}) * \dfrac{N_j + 1}{N_i + 1} if F(\mathrm{CO}) \neq 0 \,\mathrm{and CO} \neq \mathrm{then} Ce(\mathrm{CO}) = \dfrac{N_j}{N_i + 1} \end{cases} \tag{8}$$

where N_j+1 is the number of the reply requests, N_i+1 is the number of sending requests, C(CO) is the Completeness and F (CO) is the freshness. Freshness is equivalent to Age (CO) and it measures the time that elapses between reading the sensor value and delivery.

Validity is a quality parameter that measures how context information accurately corresponds to the expected value and is given by equation

$$V(\mathrm{CO}) = \frac{QualityValueGoal}{ActualQualityValue} \quad (9)$$

where *Quality Value Goal* is the expected value and *Actual Quality Value* is the measured value.

Usability is how much that piece of context information is suitable for use with the intended purpose. It considers the level of granularity of collected context information with the required level granularity.

$$UR(\mathrm{CO}) = \begin{cases} 1: ifGranularitylevel(\mathrm{CO}) \geq granularity(\mathrm{CR}) \\ 0: otherwise \end{cases} \quad (10)$$

Accuracy is a quality measure is given as:

$$A(\mathrm{CO}) = \frac{Correctnessprobability}{MinimumCorrectnessprobability} \quad (11)$$

where *Correctness Probability* is the current correctness probability of context and *Minimum Correctness Probability* is the minimum correctness probability according to the expected value.

Access Right is a quality measure that defines whether the context information provided by the context object has level of authorization to modification by other context objects. This attribute compares the access level of the context object to the access level of the context consumer.

$$AR(\mathrm{CO}) = \begin{cases} 1: ifAccessLevel(\mathrm{CO}) \geq AccessLevel(\mathrm{CR}) \\ 0: otherwise \end{cases} \quad (12)$$

Representation Consistency is a quality measure that indicates the ratio of representation format of actual context information to the expected context information as given by the context objects and is shown in equation.

$$RC(\mathrm{CO}) = \frac{Expected(\mathrm{CO})}{Actual(\mathrm{CO})} \quad (13)$$

C. Combined Confidence for Quality of Context

Combined Context Confidence for the above QoC parameters is derived from the given QoC parameter set and parameter weight. It measures the confidence in the QoC parameters provided in the domain set. Context confidence is determined by applying the context quality weight and the actual value measured by the sensing device. The combined confidence is given by the following equation;

$$Cf(\mathrm{CO})_{conf} = \sum_{i=0}^{n} (\mathrm{Cf}_{act}) * C(\mathrm{CO})_{QoC} \quad (14)$$

where $0 \leq C(\mathrm{CO})_{QoC}, Cf_{act} \leq 1$.

where $Cf\,(\mathrm{CO})_{conf}$ is the combined confidence of the context object with reference to quality

$C(\mathrm{CO})_{\mathrm{QoC}}$ is the calculated quality value for the QoC parameter of the measured low level context as given in section B. Cf_{act} is the weight for the context information as shown in equation 1.

The context weight for each context object is evaluated and quantified according to the context object contribution to the IoT situation under consideration. The weight value ranges between 0 and 1. If the weight is closer to one then there is an attached importance for the context object to the associated event. The value of $Cf\ (CO)_{conf}$ accumulates over a given set of quality of context parameter domain and is equivalent to ∂ in equation 17.

IV. Particle Swarm Optimization

PSO has been used over the decades in solving computational problems by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO was originally intended for stimulating social behavior as a stylized representation of the movement of organisms in bird flock or fish school [19]. The algorithm was simplified and was used for optimization. A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). The basic PSO algorithm can be described mathematically by the following equations:

$$\upsilon_{ij}^{t+1} = \omega\upsilon_{ij}^{t} + c_1 r_1^t(\rho_{ij}^t - \psi_{ij}^t) + c_2 r_2^t(\rho_{kj}^t - \psi_{kj}^t) \quad (15)$$

and

$$\psi_{ij}^{t+1} = \psi_{ij}^{t} + \upsilon_{ij}^{t+1} \quad (16)$$

where c_1 and c_2 are positive learning rates constants, r_1 and r_2 are random functions in the range [0, 1]; ω is a inertia weight ψ_i is the position of the particle in a problem space with D dimensions; υ_i is the rate of change of position (velocity); ρ_i is the best previous position of the swarm; the index g indicates the best particle among all the particles in the population; and t indicates the iteration number. These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered. Apart from a continuous version of the PSO, a binary version can be used in binary search spaces. This was proposed by [20] to represent velocities of particles as probabilities in the range [0..1]. This is the version that our research has adopted in the selection process of context.

A. PSO Context Selection Using QoC Combined Confidence

Imperfect context information can cause derived contexts to be inaccurate. The erroneous context information should be sieved out to avoid corrupting the decision process. It is desirable to remove erroneous sources at the earliest possible stage to minimize adapting wrong context. Context selection from the vast IoT domain uses the PSO algorithm to find the near optimal value for a context object with a highest confidence value. Each context object that is sensed within the domain can be a possible value but we know that context reliability has many other aspects to be considered. To select a context object with most reliable value using the QoC confidence PSO is defined as follows;

$$CS(\mathrm{CO})_{\mathrm{ij}} = \frac{\psi_{ij}^{\delta}}{\sum_{j=1}^{n} \psi_{ij}^{\delta}} \tag{17}$$

where $CS(CO)_{i,j}$ is the selected context object from given vector [i,j], ∂ is the confidence value used as the selection criteria, and ψ is the actual sensed value of context object. Each context object has the calculated ∂ using the QoC parameters for the context value obtained. The algorithm runs to select the desired context object.

For the PSO to perform the selection of the required context object, it was extended to deal with binary data. The context object to be selected is done through an iterative selection process with each iteration marking the selected context object. This process continues until a defined number of selected context objects is reached. Each selected context object is given a probability value proportional to the real value calculated in Equation (16) limited to the interval [0, 1].

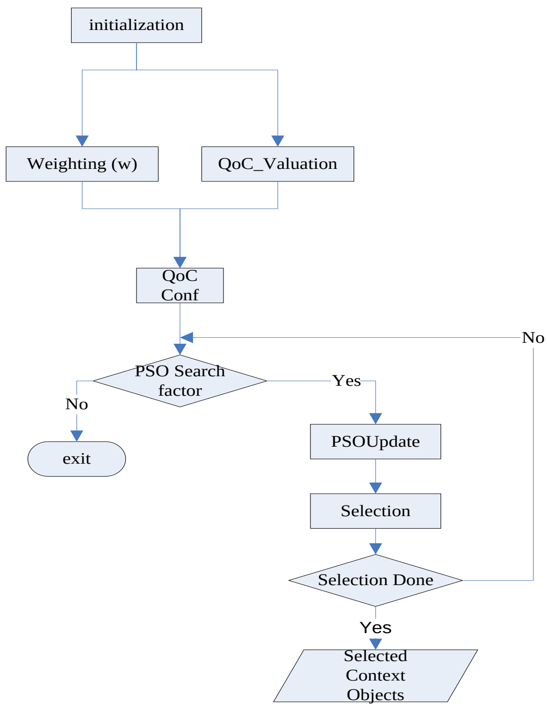

Fig. 1. Flow chart for PSO selection algorithm.

This section discusses the selection algorithm as shown in flow chart Fig. 1. The PSO algorithm performs optimization in continuous, multidimensional search space and IoT is a typical space. Our algorithm starts by the initialization process of the data in the search space. Each context value is a seen as a 'particle swarm' with its own velocity. The data set contains context objects which are all candidates in the selection process. To select the best context objects, two independent processes of weighting and QoC valuation are performed. The result is used to calculate the combined confidence which is the selection criteria for the context object. PSO uses this criteria and PSO update operator as constraints in the search process. The selected objects are displayed at the end of the algorithm.

B. QoC PSO Context Refinement Architecture

The implementation process of context refinement was achieved by taking the available or generated context information by context objects through a well defined structure. The major aim of context refinement is to obtain concrete information by evaluating the information using its attributes and attaching the result of this evaluation to the context object. As shown in Fig. 2, our research was centered on extending the context information to express its reliability and conformity to application and user relevance through QoC attributes like accuracy, trustworthiness, usability etc. The general overview of context information refinement incorporates QoC parameter assessment and assignment, context weighting and combined confidence calculation, and selection. These processes ensure only the most reliable context information is selected as demanded by the applications, devices and other applications within the IoT domain.

The QoC PSO context refinement architecture Fig. 2 uses a multi stage process to refine raw context information to concrete context information. The raw context information is obtained from the IoT domain devices, applications, users and sensors. This is the imperfect context information that is shown as raw context (context_1, context_2 ….context_n). The raw context goes into the three (3) assessment phase; context weighting, QoC Assessment and QoC Assignment.

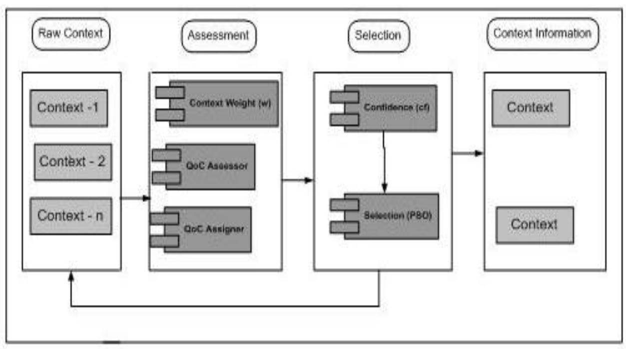

Fig. 2. QoC PSO context refinement architecture.

The context weight (w) component rates the raw context information on how close it is to the expected value. This rating is the weight that is assigned to every raw context. The QoC Assessor component uses the QoC parameters to calculate the QoC value for every context. The QoC Assigner assigns the obtained QoC value to raw contexts. In the selection phase, raw context with additional information from the previous phase is evaluated using combined confidence. The combined confidence component uses the context weight (w) and QoC assigned values to obtain confidence for each raw context. The selection (PSO) component uses this value to select the refined best value that can be used as context information. Table I summarizes the functionalities of the components in the proposed solution.

TABLE I: ARCHITECTURE SUMMARY

No.	Component Name	Description
1	Context Information Sources (C(O))	IoT context objects, devices with sensory capabilities proving context information
2	Context Weighting (w)	Context information rating according the expected value
3	QoC Assessor	QoC assessor takes into account all QoC parameters to define the quality and retains a sign value between 0 and 1
4	QoC Assigner	QoC assignment component assigns all context sources the QoC value according to the Assessor
5	Combined Confidence (cf)	This component takes in the weight and QoC values to calculate the combined confidence
6	Context Selector (PSO)	Using the combined confidence PSO selects the most reliable context information

V. EXPERIMENTAL RESULTS, ANALYSIS AND DISCUSSION

The experimental results for the algorithm showing how the proposed solution works are given in Fig. 3. The main objective for this paper is to optimize the IoT context object selection using PSO and combined confidence for QoC. The results in Fig. 3 shows that each object considered had a corresponding combined confidence value and the optimized value (selected object). It can be observed that the lower the confidence of the context object value the lower the optimized value and vice verse. This implies that only the context objects with a high combined confidence value are the most reliable context information that a context aware application can use.

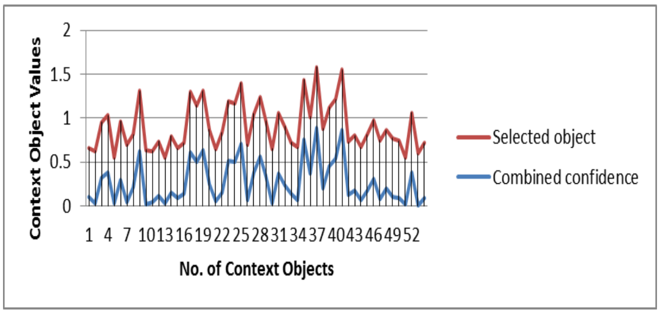

Fig. 3. Behavioral graph for combined confidence and PSO.

As Table II, III and IV can show, the proposed solution selects only context information that has the higher value of confidence. This value is concrete, more reliable and can be used in the context aware applications without the desire to accommodate erroneous information. The aim of context refinement is to produce concrete information while preserving (or even improving) the observed value. It can be seen from graphs; Fig. 4-Fig. 6 that concrete context information has the same observable behavior as the raw context. Using the context object (raw context) and combined confidence, as it can be seen, the behavioral graphs show that combined confidence does not change the raw context values but enhances it.

TABLE II: CONTEXT SELECTION SAMPLE A

No.	Context Object (CO)	Combined Confidence (Cf)	Selected Object (CS)
1	0.105259997	0.102496759	X
2	0.194313527	0.031613996	
3	0.431237350	0.316674581	X
4	0.495673109	0.387022282	X
5	0.048055955	0.026836903	
6	0.719072366	0.296552182	
7	0.542776697	0.046649585	
8	0.215699421	0.214644677	
9	0.920196714	0.623007315	X
10	0.320052379	0.016892922	

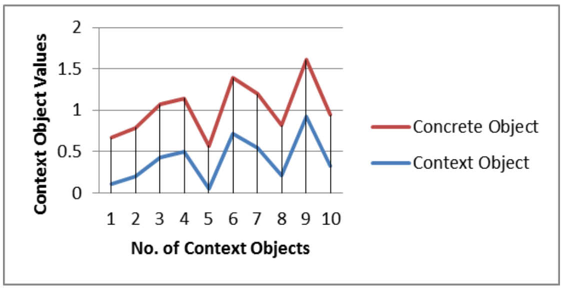

Fig. 4. Behavioral graph for context selection sample A.

TABLE III: CONTEXT SELECTION SAMPLE B

No.	Context Object (CO)	Combined Confidence (Cf)	Selected Object (CS)
1	0.293547681	0.120067177	
2	0.040611491	0.036808791	
3	0.468629052	0.150154033	
4	0.121616618	0.091731913	
5	0.151189026	0.141181028	
6	0.908507795	0.611324383	X
7	0.51413451	0.499160852	X
8	0.698034037	0.641004908	X
9	0.310203593	0.250918515	
10	0.171852046	0.059747875	

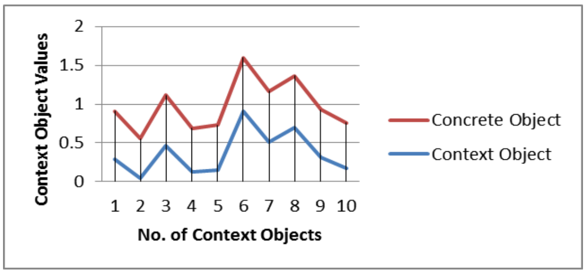

Fig. 5. Behavioral graph for context selection sample B.

TABLE IV: CONTEXT SELECTION SAMPLE C

No.	Context Object (CO)	Combined Confidence (Cf)	Selected Object (CS)
1	0.821409499	0.513884927	X
2	0.656570645	0.505278424	X
3	0.91726825	0.714333098	X
4	0.346446231	0.071973043	
5	0.695750677	0.384285933	X
6	0.783077259	0.559503987	X
7	0.364155083	0.341710853	X
8	0.317824241	0.029572886	
9	0.904086648	0.368025887	X
10	0.714009423	0.234341968	

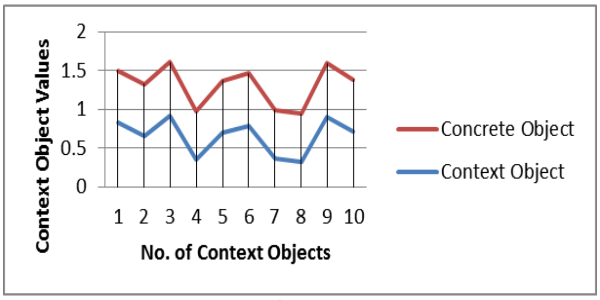

Fig. 6. Behavioral graph for context selection sample C.

In Fig. 7, the behavioral graph of combined confidence and context object shows that each value of raw context is enhanced without losing its original observed value.

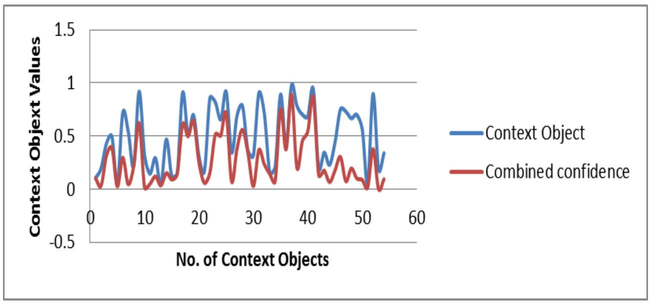

Fig. 7. Behavioral graph for combined confidence and context objects.

Fig. 8 shows the relationship between raw context (context object) and refined objects (concrete context), it can be seen that concrete refined information is adequate to represent the corresponding value of the raw context, which implies that the PSO algorithm that uses QoC to get combined confidence is surjection [21].

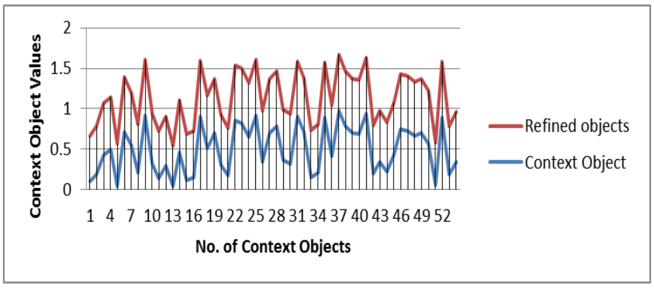

Fig. 8. Behavioral graph for refined and context objects.

Fig. 9 shows the percentage refinement of raw context information to concrete context information. In this solution 84% refinement raw context information was achieved from a randomly generated data set of raw context.

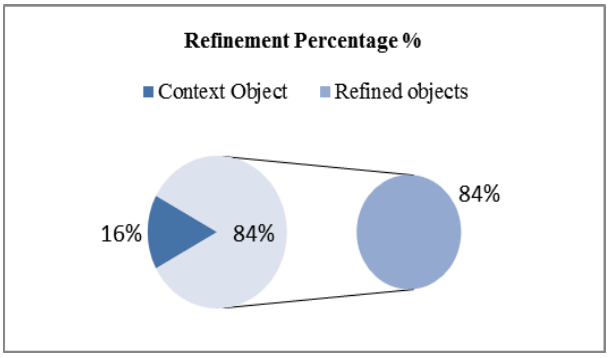

Fig. 9. Refined percentage.

VI. Conclusion and Future Works

IoT context selection optimization for context refinement has been proposed. From the results obtained, it is concluded that imperfect context information can be enriched with the right quality and relevance through the use of QoC and combined confidence. In this way context awareness in IoT can be achieved easily without accommodating imperfect context information. In our future work, we shall use our solution on a specific IoT domain with its data set and to achieve context fusion.

Acknowledgment

This research work is done under the projects funded by the Study of Proactive Complex Event Processing for Large-scale Internet of Things a project of National Natural Science Foundation of China (61371116) and National High Technology Research and Development Program of China (Program 863) No. 2012AA01A301-01

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