**Fuzzy Logic-based Robust Failure Handling Mechanism for Fog Computing**

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Fog computing is an emerging computing paradigm which is mainly suitable for time-sensitive and real-time Internet of Things (IoT) applications. Academia and industries are focusing on the exploration of various aspects of Fog computing for market adoption. The key idea of the Fog computing paradigm is to use idle computation resources of various handheld, mobile, stationery and network devices around us, to serve the application requests in the Fog-IoT environment. The devices in the Fog environment are autonomous and not exclusively dedicated to Fog application processing. Due to that, the probability of device failure in the Fog environment is high compared with other distributed computing paradigms. Solving failure issues in Fog is crucial because successful application execution can only be ensured if failure can be handled carefully. To handle failure, there are several techniques available in the literature, such as checkpointing and task migration, each of which works well in cloud based enterprise applications that mostly deals with static or transactional data. These failure handling methods are not applicable to highly dynamic Fog environment. In contrast, this work focuses on solving the problem of managing application failure in the Fog environment by proposing a composite solution (combining fuzzy logic-based task checkpointing and task migration techniques with task replication) for failure handling and generating a robust schedule. We evaluated the proposed methods using real failure traces in terms of application execution time, delay and cost. Average delay and total processing time improved by 56% and 48% respectively, on an average for the proposed solution, compared with the existing failure handling approaches.

**Index Terms**—Fog Computing, Application Failure, Dynamic Resource, Fault Tolerance, Robustness

I. INTRODUCTION

Fog computing is a distributed computing paradigm in which any device that has computation capability can contribute to application processing. These devices include mobile, network, handheld and mobile devices [1]. Cloud computing has latency issues in which time-sensitive real-time application execution cannot be performed. Hence, Fog computing has emerged; it can process user application requests with minimum latency, since Fog devices are located close to the users. Applications in a smart environment must be able to respond instantly, without delay. Some example of these kinds of applications are smart cars, augmented reality applications, online multiplayer games and emergency response applications.

Fog is a highly distributed environment in which numerous autonomous devices contribute to processing application requests; these are known as Fog devices [1]. The contributing devices can produce a financial benefit by allowing the Fog platform to use their resources for Fog application processing [2]. Unlike cloud resources, fog computing resources are not managed service, hence, they have high probability of failure. Furthermore, the devices in Fog environment are not completely dedicated to Fog application processing [3]. Hence, there is no guarantee that devices are always available. The device can even fail after starting the processing of the Fog application. In such a scenario, it is important to make the scheduling of the application robust for successful execution in the Fog environment, despite any failure of the Fog devices at this stage. This will reduce the impact of any application failure in the Fog environment.

Without ensuring proper failure handling mechanisms, it is not possible to run time-sensitive real-time applications in the Fog environment. This is because the failure of a Fog application or device might contribute to the high rates of delay which lead to the execution of the application being unsuccessful. Thus, this is an important and challenging area for research. The need for the successful execution of Fog applications in the dynamic Fog environment motivated us to explore the reasons for failure and to investigate possible solutions.

In order to meet the time sensitivity of the applications, handling failure in the Fog environment is an important and challenging task [4]. For application processing, the cloud computing environment mostly depends on the cloud data centre [5] in which the rate of failure is not that high compared with the Fog environment. Fog devices are controlled by decentralised entities while cloud data centres are managed by some central entities. Hence, predicting application failure in the cloud environment is less complicated compared with such predictions in Fog computing. In the Fog environment, it is difficult to predict the failure of the computation resources due to the unstable characteristics of the available resources in the Fog devices. Thus, a robust scheduling algorithm needs to be developed. On the other hand, to prove the correctness of the robust scheduling, an evaluation with real failure traces is required. Robust scheduling is a mechanism by which application will be executed in a way in which there will no opportunity for application failure. Even if there is a failure...
robust adaptation mechanism can bring back the system to stable state. To ensure this, applications might need to execute in different places at the same time, in order to avoid the risk of failure.

Two methods are available for handling failures in service-oriented computing; these are proactive and reactive failure handling mechanisms [9] [7]. Proactive failure needs to be considered in a highly distributed environment in such a way that failure handling has taken place before occurrence of the failure. However, proactive failure handling will not always be suitable because some failures might occur beyond our prediction. This is because of the possibilities of device malfunction, user interruption and uncertain changes in resource availability. Therefore, we need to consider reactive failure handling which usually takes place after the failure has occurred. Due to the unstable nature of Fog devices, applying either of the methods is not always useful for ensuring the successful execution of the application in a time-sensitive manner. Hence, we used task replication methods, along with proactive and reactive failure handling methods.

In this paper, we propose a composite solution by using proactive and reactive failure handling methods with replication. The key contributions of this paper are as follows:

1) We propose a fuzzy logic-based method to deal with unpredicted and predicted failures.
2) Our failure handling method considers time sensitivity of the application, as well as dynamic changes in the available resources in the devices.
3) We evaluate the proposed failure handling method using real failure traces.

The rest of the paper is organised as follows: Section II presents related literature of failure handling mechanisms in the P2P system, a cluster, a grid, the cloud and the Fog computing paradigm. Section III discusses the application scenario for the proposed solution. Section IV discusses the definition of the problem. A brief description of various resources failures and their solutions is presented in Section V. Section VI gives a detailed description of the proposed Fuzzy logic-based solution. Section VII discusses the experimental setup and evaluation technique. Section VIII presents experimental results and discussion. Finally, Section IX concludes the paper.

II. RELATED WORK

This section describes some related work on failure handling mechanisms in different distributed computing paradigms. We chose to survey failure handling methods in order to verify the uniqueness of our research. We reviewed some methods that are being used for the P2P system, as well as cluster, grid, cloud and Fog computing paradigms, in order to make the system fault-tolerant.

A. Failure handling in P2P System

Samant and Bhattacharyya [8] examined the impact of node failure on the accessibility of resources on P2P networks. Their work examined how search efforts, the topology of the network and redundant resources can influence accessibility when various level node failures take place. Vanthournout and Deconinck [9] proposed three strategies to realise the use of self-organisation mechanisms for failure handling and failure detection.

Lin et al. [10] presented an efficient fault-tolerant approach for the super-peers of peer-to-peer (P2P) file-sharing systems. Mawood-Yunis et al. [11] identified the disconnection failure problem, due to temporary semantic mapping faults, and proposed a game theory based Fault Tolerant Adaptive Query Routing (FTAQR) algorithm to resolve it.

B. Failure handling in Cluster

Li and Lan [12] proposed FT-Pro, an adaptive fault management mechanism that optimally chooses migration, checkpointing or no action to reduce the application execution time in the presence of failures based on the failure prediction. Various methods have been used in cluster computing to predict failure event. These methods include genetic algorithms [13], rule-based data mining [14]–[16] and Markov chain [17]. Many other works focus on fault management techniques which are based on prediction. Leangsuksun et al. [18] proposed a predictive failure handling mechanism which scheduled deliberate job checkpointing and migration. In another work, Castelli et al. [19] employed a different approach to failure prediction. In their approach, they first predicted the resource exhaustion failure proactively and then conducted software rejuvenation. To maximise system throughput, Oliner et al. [20] used the coordinative checkpointing strategy that optimistically skips a checkpoint when no failure prediction exists in the near future. Chakravorty et al. [21] proposed software-based prediction of failure which basically migrates a task before the failure actually occurs.

C. Failure handling in Grid

Hwang and Kesselman [22] proposed a flexible failure handling framework for the grid which is comprised of two phases: failure detection and recovery phases. In the failure detection phase, an event notification mechanism reports failures. A failure handler deals with the failures at two levels: the task level and the workflow level. Task level failures are handled by retrying, checkpointing and replication. At the workflow level, they are managed by alternative task and redundancy. Jin et al. [23] proposed the Fault Tolerant Grid Platform (FTGP) approach from the perspective of grid users, taking the nature of grid faults into account.

Lee et al. [24] proposed a resource manager for optimal resource selection. The proposed resource manager automatically selects a set of optimal resources from candidate resources which achieve optimal performance using a genetic algorithm with a fault tolerance service that satisfies QoS requirements. Lee et al. [24] implemented a fault detector and a fault manager which will handle failure by job migration, using a checkpoint. Kandaswamy et al. [25] proposed a fault-tolerance technique using over-provisioning and migration for computational grids. Khoo and Veeravalli [26] proposed a failure handling mechanism based on pro-active failure handling strategies for grid environments.
D. Failure handling in cloud computing

Much research on handling failures in the cloud environment has been undertaken to provide a failure-prone environment. Two review works [6], [7], in which all kinds of failures were categorised into reactive and proactive failure methods, extensively evaluated failure handling mechanisms in the cloud. Reactive failure mechanisms were further divided into three sub-categories: checkpointing, replication and logging. While Virtual Machine (VM) migration was considered as proactive failure management, Gill and Buyya [6] suggested continuous monitoring of resource allocation to manage failures in the cloud environment during operation. Sharma et al. [7] point out that predicting resource behaviour is critical in the cloud environment.

Sharma et al. [27] proposed a failure-aware VM consolidation technique based on exponential smoothing. They employed checkpointing and migration of VM in their proposed method. Luo et al. [28] proposed a Markov-based model to examine failures in large-scale cloud computing systems. They employed reliability-aware resource scheduling to improve fault tolerance. Although cloud computing is a mature technology, it still lacks service reliability. Hence, Buyya et al. [29] suggested investigating failure-aware provisioning and reliability-aware service management mechanisms for the cloud computing environment.

E. Failure handling in Fog computing

Existing failure handling methods in P2P, distributed and cloud computing mainly scale infrastructure to utilise extra resources to cover failure but in Fog computing, fault tolerance is challenging due to some unfavourable factors, such as resource constraints and multiple procedures [30]. Most of those methods considered only one failure handling method (for example, checkpointing or replication or resubmission) for fault tolerance [31]. Also, they did not consider any time sensitivity of the user request [31]. Hence, some researchers proposed new methods for failure handling in the Fog computing environment [31], [32].

A Fault-Tolerant Scheduling Method (FTSM) was proposed by Alarifi et al. [31] for the Fog-Cloud environment. In their approach, the system submits time-tolerant requests to the cloud and time-sensitive requests to the edge devices. FTSM finds the checkpoint interval based on the operation time between failures for the devices. However, Alarifi et al. [31] did not consider any prediction of the failure for devices based on the fluctuating availability of computation resources in the devices. Tajiki et al. [32] proposed the Heuristic Fast Failure Recovery (HFFR) algorithm for software-defined service function chaining for Fog computing with failure consideration. The main idea of their proposed method is to find failure probability based on the predefined threshold. Similar to FTSM, HFFR did not consider the dynamic changes in the available resources. In addition, neither of the works considered real failure traces for evaluating their proposed methods. Battula et al. [33] proposed an efficient resource monitoring service for Fog computing which suggested failure handling is essential for efficient resource management in the Fog environment.

In summary, existing failure handling methods in Fog computing did not take into account fully the dynamic availability of Fog resources. In this paper, we propose a combined approach of proactive and reactive failure handling with task replication to tackle highly dynamic behaviour of Fog resources. Thus, this research was carried out to propose a composite solution of utilising proactive, reactive and replication failure handling methods with dynamic changes of the resources in the Fog devices. The bivalent proposition of the Fuzzy logic technique motived us to employ this approach for failure handling.

III. FAILURE ISSUES AND SCENARIO

In this section we describe the application scenario and the research problem. We also discuss the reasons for resource failure and some possible solutions for handling failures in the Fog environment.

A. Application Scenario

To demonstrate the problem solved in this paper, an application scenario is presented in this section. Let us assume that an emergency vehicle is using a smart transportation application and moving from point A to point B. The vehicle has to choose the shortest route to the destination. To fulfil this requirement the system needs to process data generated or stored in a dash cam, surveillance camera and sensors. Based on the traffic conditions, the following actions need to be taken: (i) inform other vehicles ahead that an emergency vehicle is approaching; (ii) override signals if there are multiple road junctions along the way; (iii) do the relevant processing in the Fog devices, and (iv) take action following the processing. The overall scenario and system architecture is presented in Figure 1.

Other incidents might also occur while the emergency vehicle is enroute. The system should act promptly to minimise
the delay in reaching the destination. Here, the system needs to process data from sensors, as well as video data from dashcams and surveillance cameras. All of the processing for the above application scenarios is done in Fog devices to comply with the need for time sensitivity. Therefore, the utilisation of processing power and on-time processing are important. It is possible to ensure time sensitivity of the application by distributing the application workload among Fog devices. But the issue is what will happen if the Fog node has failed? We need to ensure that the outcome of the application should meet time-sensitive requirements in which the robustness of the scheduling approach will be assured.

Robustness is a feature of the scheduling process in which application execution will be successful by ensuring time sensitivity, even if the resource has failed, any errors have occurred in the system components or any erroneous input has taken place. In our application scenario, the application always requests the completion of the processing by defining a deadline. However, our concern is how to deal with the failure of the resources during operation. We are specifically focused on minimising the impact of the failure on the applications, due to resource failure, by handling the situations in which Fog device resources have failed.

B. Problem Definition

This research was carried out to solve the following problem: How to meet user requirements for applications in the Fog environment, with consideration of device failure, in order to satisfy any time-sensitive requirements of the application, while available resources in the devices are changing dynamically?

Scheduling all related tasks to Fog devices is not such a complicated task if we can assume that all devices are up and running, and there are no chances of their failure. But, in reality, the chance of failure in the Fog environment is very high since the devices are not dedicated to running Fog applications. On the other hand, most of the devices in the Fog depend on wireless connectivity. Also, the devices are mobile and are moving frequently from one cluster to another. Next, most of the Fog devices are not stationary, meaning that the devices have limited battery power. Furthermore, the application might be interrupted by the owner of the devices (for example, the owner turns off the device for some reason; the owner does not want to participate at that moment or the owner wants to run another application which requires some resources to be freed up). Due to all of the above reasons, the chances of failure of the computation resources are very much higher than in any other distributed system. To ensure the robustness of the scheduling algorithm, we need to deal with resource failures in a way that the application user would not affected.

C. Resource Failure and Counter-measures

The resources could fail in the Fog environment for many reasons. The reasons for failure can be categorised, such as the termination of the application to run the native application, network failure, the device being moved to another cluster, power outage, human interruption, software and hardware failure, and network attacks. Due to the mobility and dynamicity of the available resources in the devices, we can categorise all types of failure into two basic types: (i) unpredicted/immediate failure and (ii) predicted failure.

We can handle failures in two different ways. Firstly, we can manage the resource failure after it took place; this is referred to as reactive failure. Secondly, it is possible to have countermeasures before the occurrence of the resource failure; this is known as proactive failure handling. Both types of failure handling mechanism have different approaches to manage resource failures.

In a reactive failure handling mechanism, we can employ checkpointing and replication. In application checkpointing the state of the application is stored in reliable storage and, if the application has failed, it does not need to rerun the application from the beginning. It will start the application from the point where the latest state has been saved. There are two types of checkpointing: i) coordinated or periodic checkpointing and ii) uncoordinated or random checkpointing. In coordinated checkpointing, the point should be consistent for the processes. In uncoordinated checkpointing, each process checkpoints its state. The other type of reactive failure handling mechanism is replication which always run replicas of the running processes in different devices.

The basic way to solve immediate failure is re-running the whole application but this is not the optimum way to solve the problem. For example, if a certain percentage of processing is completed, there is no point in processing the same portion of the application. Hence, the only solution for immediate failure is checkpointing. Some researchers have argued that checkpointing is not a good solution for the Fog environment because the Fog is a highly dynamic environment. Yi et al. suggested that replications are more suitable for the Fog but multiple Fog nodes would need to be working together. Madsen et al. suggested using checkpointing for the Fog which would save computation time for the faulty tasks. Some researchers used checkpointing in the Fog as a fault-tolerant technique. We needed to ascertain if there were any way to accommodate checkpointing in the Fog environment. To do that we needed to evaluate our solution in simulation and also in a real environment. We evaluated our proposed method in a simulated environment with real failure traces.

In a proactive failure handling process, we can employ the migration process before the resource failed. Since the Fog is for time-sensitive applications, we were required to migrate the application without disconnecting devices. Hence, we needed to employ live migration for this process. Two basic types of migration are i) pre-copy migration and ii) post-copy migration. In post-copy migration, application migration needs to be initiated by suspending the application at the source which will increase down-time. To minimise downtime, pre-copy migration needed to have been employed. To resolve the predicted failure, we could have employed pre-copy live migration. Once we could predict that an application was going to fail then we could migrate the application to another Fog device. But again, the question is raised: how to
decide when and where to migrate? However, this research only dealt with when to migrate, not where to migrate to. To ensure the robustness of the scheduling algorithm, we needed to handle both predicted and unpredicted failures which would minimise their impact.

IV. FUZZY LOGIC-BASED FAILURE HANDLING MECHANISM

To handle predicted and unpredicted failure we employed the fuzzy logic-based solution. Classical logic usually has a bivalent proposition, which may be true or false in principle. On the other hand, fuzzy logic can represent actual membership of both true and false for a function. Some propositions might be true and false to a certain degree, rather than being true or false only. For example, for a Fog device, mobility, response time and power availability might cause the failure of a device. However, the chances of failure completely depend on the membership of each parameter (for example, mobility, response time and power availability). To represent the exact degree of membership of each parameter, a fuzzy logic-based approach was undertaken. If the unpredicted failure for a Fog device were high then the Fog device would be flagged as unreliable. To handle failure for unreliable Fog devices, replication was used to ensure the robustness of the scheduling algorithm.

A predicted failure handling mechanism basically acts before the resource failure takes place. However, due to decentralised management of the Fog devices, an application might have failed but this was beyond our prediction. Thus, an unpredicted failures handling mechanism allows seamless application processing. Frequent unpredicted failures caused by a Fog device will trigger replication to ensure successful application execution. Therefore, to ensure a reliable application processing environment, all three approaches (predicted failure, unpredicted failure and replication) need to be considered. Figure 2 shows what action will be taken after calculating the failure score.

![Fig. 2: Proposed failure handling mechanism.](image)

Over utilisation of resources always causes failure. Suleiman and Venugopalan [38] modelled elasticity rules for the cloud when the resource has been scaled, when utilisation is either 75% or 80%. This indicated that the chances of failure was high when the utilisation was more than 80%. Hence, we assumed that 80% to 100% utilisation was unsafe and service migration needed to have been triggered. In another work Liu et al. [39] mentioned that the chances of server crash were high when utilisation was more than 60%. Therefore, they have chosen a workload threshold of 50% to 70%. Al-Haidari et al. [40] revealed that the upper threshold for cloud resources utilisation should be 70% to 90%. Based on these studies [38]–[40] we assumed that less than 50% utilisation was safe and it was necessary to checkpoint in case of failure if the utilisation were 50% to 80%. A user could change these thresholds while they were being implemented in a real environment through the proposed algorithm.

A. MRP score calculation for unpredicted failure

To find an unpredicted failure, the system always calculates the degree of failure by calculating membership of the following parameters: (i) device mobility, (ii) device response time and (iii) device power availability.

Based on the degree of failure, the system will decide how frequently checkpointing needs to be undertaken. Based on the percentage of the device movement, we defined how readily the device could be completely moved to another network. Device mobility can be represented as $D_m$, which could be 0% to 100%. Device response time always maps with required response time to meet the application time sensitivity. For example, to complete an application request, the device response time should be 2ms but the device is responding in 1ms; therefore, the degree of failure is within the group of 0%. On the other hand, if the device response time suddenly changed to 2.5ms then the degree of failure is within the group of 100% since it is not meeting the application time-sensitive requirements. Device response time can be represented as $D_r$ which could be 0% to 100%. Similarly, the power available score can be calculated based on the power that is required to complete the submitted application. All the parameters of device characteristics are transformed into a normalised range [0 to 1] during fuzzification. Fuzzy logic usually includes three phases: fuzzification, fuzzy inference and defuzzification. The fuzzy sets for the above parameters are as follows:

- Device mobility: $D_m \in \{\text{Low, Normal, High}\}$
- Device response time: $D_r \in \{\text{Fast, Normal, Slow}\}$
- Device power: $D_p \in \{\text{Rich, Standard, Poor}\}$

Using Equation 1 the value can be normalised to fall in the interval [0 to 1].

$$D_x = \frac{D_x - \alpha_x}{\beta_x - \alpha_x}$$  \hspace{1cm} (1)

In the Equation 1 $D_x$ is the numerical value of $x$ where $x$ is either mobility, response time or power. The value of $x$ is within the range of $\alpha_x$ to $\beta_x$. The normalised value of the parameters’ mobility, response time and power were calculated for further operation. The degree of membership of each parameter is shown in Figure 3.

The mobility parameter of 0% to 50% is considered as low mobility; 30% to 90% is normal mobility and 70% to 100% is considered to be high mobility. Until 30% mobility membership, we considered that the system was in safe zone.
However, at the point of 30%, the mobility membership was low and was decreasing, and normal mobility membership was increasing. At the point of 50%, the low mobility membership was 0 and normal mobility membership was 1. However, at the point of 70% normal mobility, membership decreased and became 0 at 90%. On the other hand, a 70% high mobility score, which started to increase and reach 1 at 90%, meant that the device was about to fail. A similar approach was employed for response time and membership of the power availability parameters. Based on the membership of each parameter, fuzzification was completed in the Fuzzy Interference System (FIS). To develop FIS we used the jfuzzylogic toolbox [41].

The membership function for low, normal and high mobility is shown in Equations 2, 3 and 4. A similar equation is used for response time and power parameters.

\[
\mu_{mL}(x) = \begin{cases} 
0, & x > d \\
\frac{d - x}{d - c}, & c \leq x \leq d \\
1, & x < c
\end{cases}
\]

(2)

\[
\mu_{mN}(x) = \begin{cases} 
0, & (x < a) \text{ or } (x > d) \\
\frac{x - a}{b - a}, & a \leq x \leq b \\
1, & b \leq x \leq c \\
\frac{d - x}{d - c}, & c \leq x \leq d
\end{cases}
\]

(3)

\[
\mu_{mH}(x) = \begin{cases} 
0, & x < a \\
\frac{x - a}{b - a}, & a \leq x \leq b \\
1, & x > b
\end{cases}
\]

(4)

We used max function as an accumulation method by which the fuzzy outcome of a particular application is represented as \( X_i \).

Fuzzy rules: Based on the behaviour of the system fuzzy, rules were generated. If any of the parameters were high, the system would not have been capable of running any application. More clearly, if a system were highly mobile, there was a high chance of resource failure in that device. In the same way, if response time or power membership were high, then resource failure in that particular device was also high. For this particular instance the rule should be as follows:

- If \( D_m \) is high or \( D_r \) is slow or \( D_p \) is poor then \( UF_{mrp,m} \) is high

In the above rule, \( UF_{mrp,m} \) represents an unpredicted failure score for application \( m \). In order to consider some devices as being in a safe zone, all scores of all parameters should have safe zone scores with a 0% to 50% variation. For this particular instance, the rule is as follows:

- If \( D_m \) is low and \( D_r \) is fast and \( D_p \) is rich then \( UF_{mrp,m} \) is low

To define device membership in the checkpoint zone, mobility should be low or normal, response time should be fast or normal, and power availability should be rich or standard. The mobility membership should not be high; response time should not be slow and power should not be poor, to be in the checkpointing zone. In addition, mobility should not be low, response time should not be fast and power should not be rich at the same time. To represent the situations described above, we defined seven different rules. An example of such a rule is given as follows:

- If \( D_m \) is low and \( D_r \) is fast and \( D_p \) is standard then \( UF_{mrp,m} \) is normal

Fuzzy inference and defuzzification: To generate an mrp score we used 0% 50% as a low score, 50% to 80% as a normal score and 80% to 100% as a high score (See Figure 3). A Center of Gravity (CoG) defuzzification method was used for calculating the mrp score. The equation for CoG is shown in equation 5.

\[
UF_{mrp} = \frac{\sum_{i=1}^{n} X_i \times \mu_i}{\sum_{i=1}^{n} X_i}
\]

(5)

In the above equation \( n \) is the number of rules needing to be triggered. \( \mu_i \) is the singleton value which refers to the maximum score for a particular parameter. The defuzzification value for an application was used to make decisions about application failure handling (mrp score).

B. CPMNR score calculation for predicted failure

Some failures can be predicted based on the following criteria:
• Effect on processing based on the current CPU utilisation
• Effect on processing based on available power in the device
• Effect on processing based on device mobility
• Effect on processing based on network communication (Device is capable of completing the request but network communication might be the cause of not meeting time-sensitive requirements)
• Effect on processing based on device response time

All device behaviour parameters were transformed into a normalised range [0 to 1] during fuzzification. The fuzzy sets for the above parameters are as follows:

- CPU utilisation: \( D_{mc} \in \{\text{Low, Normal, High}\} \)
- Device power: \( D_{mp} \in \{\text{Rich, Standard, Poor}\} \)
- Device mobility: \( D_{mn} \in \{\text{Rich, Standard, Poor}\} \)
- Network communication: \( D_{mn} \in \{\text{Fast, Medium, Slow}\} \)
- Response time \( D_{mr} \in \{\text{Fast, Normal, Slow}\} \)

Using Equation 6, the value can be normalised to fall into the interval [0 to 1].

\[
D_{mx} = \frac{D_{mx} - \alpha_{mx}}{\beta_{mx} - \alpha_{mx}} \quad (6)
\]

In the Equation 6, \( D_{mx} \) is the numerical value of \( mx \) where \( mx \) is either CPU utilisation, power, mobility, network communication or response time. The value of \( mx \) was within the range of \( \alpha_{mx} \) to \( \beta_{mx} \). The normalised value of the parameters’ CPU utilisation, power, mobility, network communication and response time was calculated for further operation. The degree of membership of each parameter is shown in Figures 5.

The CPU utilisation parameter 0% to 50% was considered to be low CPU utilisation; 30% to 90% was normal CPU utilisation and 70% to 100% was considered to be high CPU utilisation. Until 30% CPU utilisation membership, we considered that the system was in safe zone. However, at the point of 30%, low CPU utilisation membership decreased and normal and high CPU utilisation membership increased. At the point of 50%, low CPU utilisation membership was 0 and normal and high CPU utilisation membership was 1. However, at the point of 70%, normal CPU utilisation membership started to decrease and became 0 at 90%. On the other hand, a 70% high CPU utilisation score starting to increase and reaching 1 at 90% meant that the device was about to fail due to the over utilisation of the CPU. A similar approach was employed for power availability, mobility, network communication and response time parameters. Based on the membership of each parameter, fuzzification was undertaken in the FIS system. Similar to the calculation of the MRP score, we used Equations 2, 3 and 4 for the membership function of low, normal and high for CPU utilisation, power availability, mobility, network communication and response time parameters.

Similar to the MRP score calculation we used the max function as an accumulation method by which the fuzzy outcome of a particular application is represented as \( X_i \).

Fuzzy rules: Based on the behaviour of the system, fuzzy rules have been generated. If any of the parameters are high the system will not be capable of running any application. More clearly, if a system has high CPU utilisation, there is a high chance of application failure in that device. In the same way, if power, mobility, network communication and response time membership are high, then application failure in that particular device will be high as well. For this particular instance the rule should be as follows:

- If \( D_{mc} \) is high or \( D_{mp} \) is poor or \( D_{mn} \) is high or \( D_{mr} \) is slow then \( PF_{cpmnr} \) is high

In the above rule, \( PF_{cpmnr} \) represents the unpredicted failure score for application \( m \). In order to consider some devices as being in a safe zone, all scores of all parameters should have safe zone scores which are within 0% to 50% variation. For this particular instance the rule is as follows:

- If \( D_{mc} \) is low and \( D_{mp} \) is rich and \( D_{mn} \) is low and \( D_{mr} \) is fast and \( D_{mr} \) is fast then \( PF_{cpmnr} \) is low

To define device membership in a checkpoint zone, CPU utilisation should be low or normal, power availability should be rich or standard, mobility should be low or normal, network communication should be fast or medium and response time should be fast or normal. The CPU utilisation membership should not be high, power should not be poor, mobility membership should not be high, network communication membership should not be slow and response time should not be slow to arrive in the checkpoint zone. Also, CPU utilisation should not be low, power should not be rich, mobility should not be low, network communication should not be fast, and response time should not be fast at the same time. To represent the situations described above, we need to defined 31 different rules. An example of such a rule is given as follows:

- If \( D_{mc} \) is low and \( D_{mp} \) is rich and \( D_{mn} \) is low and \( D_{mr} \) is normal then \( PF_{cpmnr} \) is normal

Fuzzy inference and defuzzification: To generate the cpmnr score we used 0% 50% as a low score, 50% to 80% as a normal score and 80% to 100% as a high score (See Figure 5). The Centre of Gravity (CoG) defuzzification method was used for calculating the cpmnr score. The equation for CoG is shown in Equation 7.

\[
PF_{cpmnr} = \frac{\sum_{i=1}^{n} X_i \times \mu_i}{\sum_{i=1}^{n} X_i} \quad (7)
\]

In the above equation \( n \) is the number of rules needing to be triggered. \( \mu_i \) is the singleton value which refers to the maximum score for a particular parameter. The defuzzification value for an application was used for making decisions about the predicted application failure handling (cpmnr score).

C. Replication

Replication of the application only applies if the rate of unpredicted (immediate) failure is high. The failure rate cannot be calculated within the execution of a few application attempts. Due to this we considered at least 10 application executions before deciding whether replication was required or not. The overall process of the failure handling process is presented in Figure 6.
Algorithm 1 Fuzzy-logic-based failure handling (FLBFH).

Input: App\[id, D_m, D_p, D_mce, D_mp, D_mm, D_mp, SD_{ft}, Ac\]
Output: Ac\[\{App_{id}, Actions\}]

for all App\[id\] do
  Calculate degree of changes in mobility
  Calculate degree of response time changes
  Calculate degree of power profile changes
  Calculate degree of CPU utilization changes
  Calculate degree of changes in network comm
  Calculate degree of failure (d\_f)
  if d\_f \geq 50 and d\_f \leq 80 then
    Ac\[\{App_{id}, Checkpoint\}]
  else if d\_f \geq 80 and d\_f < 100 then
    Ac\[\{App_{id}, Migrate\}]
  else if d\_f \geq 100 then
    Ac\[\{App_{id}, CheckpointRecover\}]
  end if
  ASD\_f = (SD_{ft} + d\_f)/Ac
  if ASD\_f \geq 50 and Ac > 10 then
    Ac\[\{App_{id}, Replicate\}]
  end if
end for
return Ac\[\]

V. EXPERIMENTAL SETUP AND EVALUATION TECHNIQUE

A. Failure Modelling

Since no failure traces are available for the Fog, we used failure traces from the Failure Trace Archive (FTA) [42]. There are 27 real failure traces available in FTA. Most of those traces have two events: failed or not failed (available). Among them, only Los Alamos National Laboratory (LANL) [43] has failure traces with reasons such as CPU failure, power failure or network failure. Therefore, we selected LANL failure traces to model failure in the Fog environment. LANL has failure traces for nine years (1996 to 2005) which consist of 4750 nodes that...
form 22 High-Performance Computing (HPC) systems [43]. This trace has the records for every failure that takes place within the system and which needs administrator attention. We selected those devices from LANL failure traces which had comparatively high failure rates compared with other devices. Those selected devices did not have failure traces for the year 1996 and 2005. Due to that, we used failure traces from 1997 to 2004. The Fog environment consists of numerous nodes, each HPC nodes being considered as a single Fog node. The LANL failure traces only have the information as to whether the resource failed or not. By keeping the Fog device characteristics intact, we utilised the failure information of the Fog node during simulation-based experiments. Hence, it is logical to use LANL failure traces in our experimental scenario.

B. Experimental Setup

In order to control over the experimental environment, we chose simulation to evaluate the proposed method. We adopted a simulation environment and performance parameters from our previous works [44] [45]. In addition, we modelled a realistic Fog environment by extending the CloudSim [46] toolkit, similar to our previous work. All submitted tasks followed deadlines which varied dynamically from 10% to 80%, similar to our previous work [45]. Successful execution of application by maintaining deadlines indicated successful processing.

C. Performance Metrics

All the performance metrics were adopted from our previous works [44], [45].

Delay: We considered the delay between the user to the Fog resources. Delay is the time between task submission and the starting of task execution. It can be calculated as follows:

\[ d^x_t = E^x_{st} - U_S \]  

(8)

In Equation (8), \( d^x_t \) denotes the delay for the \( x \) Fog device which is involved in task execution. \( E^x_{st} \) is the task start time and \( x - U_S \) is the time when the user requested the execution of the task.

Processing time: Processing time is the required time to process a task. It is the time between the task processing start time \( p_{st} \) and the task processing end time \( p_{en} \) which can be calculated by using the Equation (9)

\[ Pt^x_t = p^{x}_{en} - p^{x}_{st} \]  

(9)

In the above equation, \( x \) is the Fog device which is involved in task execution, and \( Pt^x_t \) is the processing time for task \( t \).

Processing Cost: We considered connectivity and messaging costs for processing costs. These costs are based on the AWS IoT pricing model. Cost is from $1 to $1.65 per million messages for messaging and from $0.08 to $0.132 for connectivity cost for per million minutes for various regions. We considered the price that has been allocated for the Sydney region. Processing cost can be calculated as follows:

\[ P_{ct} = \sum_{k=a}^{n} (M_c + C_c) \]  

(10)

In the above Equation, \( M_c \) is the messaging cost and \( C_c \) is the connectivity cost and \( P_{ct} \) is the total processing cost. We calculated cost for Fog device \( a \) to Fog device \( n \).

D. Evaluation Technique

We compared the proposed FLBFH with two recent works HFFR [32] and FTSM [31]. Since those two works were implemented in a different simulation environment and did not consider real failure traces, we adopted the key idea of both proposed methods to fit with our simulation environment and failure traces. We compared both methods with our proposed method in the results and discussion section to show the improvement of the FLBFH failure handling method over previously proposed methods.

VI. RESULTS AND DISCUSSION

We took eight years of failure traces to perform simulations and simulate each year’s failure traces separately for HFFR, FTSM and the proposed FLBFH methods. Performance comparison of each metric is presented below in different subsections.

A. Delay

We measured average, maximum and minimum delays for each task, as shown in Figure 7, 8 and 9. The average delay for the proposed FLBFH method was improved by around 52% and 58% for HFFR and FTSM respectively, on an average for all failure traces (Figure 7).

![Fig. 7: Average delay for different failure traces.](image)

For the failure traces of the year 2000, 2001 and 2003, the improvement was around 51% for HFFR compared with the proposed method. The maximum improvement was found for
the 2004 failure traces which was 54%. Delay improvement for the rest of the failure traces was between 52% to 53%. On the other hand, compared with FTSM, the maximum improvement was 60% for the 2003 failure traces in the proposed method. The minimum delay improvement found for the 2001 failure traces compared with the FTSM, was 55%. However, the improvement was 59% for 1998, 2000 and 2002 failure traces, and 56%, 57% and 58% respectively for 1997, 1999 and 2004 failure traces. The delay improvement was different because of the difference failure handling technique. However, our proposed FLBFH method performed better over both HFFR and FTSM methods.

The maximum delay for the proposed FLBFH method was improved by around 50% and 56% for HFFR and FTSM respectively (Figure 8).

For all failure traces, the maximum delay was improved 49% to 50% in the proposed method, compared with the HFFR method. On the other hand, the improvement was in between of 55% and 56% in the proposed method, compared with the FTSM method. Maximum improvement was found over FTSM method for average delay and the same trend was found for maximum delay.

The minimum delay was more in FLBFH for most of the cases, as compared with HFFR and FTSM (Figure 9). Compared with HFFR, it was 19% more, while it was 13% more for FRSM on an average, for all failure traces. However, for 1997, 1998 and 2001, the failure traces minimum delay improved compared with FTSM, the improvement being 17% to 20%. Since the average delay was improved for the proposed algorithm, the minimum delay will not have much effect on application processing.

B. Processing time

There is no significant difference in the average processing time for HFFR and FTSM, compared with the proposed FLBFH method (Figure 10). However, the number of failed tasks was less in the proposed FLBFH method. Since the proposed method used a Fuzzy-logic based approach for failure handling and prediction, it was able to handle failure more efficiently, with a resulting improvement in the total processing time.

On average, the total processing time improved by 51% and 45% for the FLBFH method, compared with HFFR and FTSM respectively as shown in Figure 11. Compared with HFFR, the improvement was around 50% to 51% and compared with FTSM, it was around 44% to 46%. Total processing time improved in the proposed method because the number of failed tasks in the proposed method was fewer which provided better failure handling and robust scheduling.
less chance of failure.

further by selecting more appropriate Fog devices which have
resource allocation. The proposed method can be improved
the real Fog computing environment, as well as power-aware
the implementation and evaluation of the proposed method in

delay and total processing time which were 56% and 48%
proposed failure handling method was evaluated using real
proposing a Fuzzy-logic-based failure handling method. The
resources; it helps to improve delay and processing time by
total number of application failures due to the failure of the
failure traces. On the other hand, FTSM had around 44%
higher cost compared with FLBFH. This indicates that the
number of failed tasks was higher in HFFR and FTSM,
compared with the proposed FLBFH method.

C. Cost

The total processing cost was less for the proposed FLBFH
method, compared with HFFR and FTSM, as shown in Figure
12. HFFR had around 77% higher cost on average for all
failure traces. On the other hand, FTSM had around 44%
highest cost compared with FLBFH. This indicates that the
number of failed tasks was higher in HFFR and FTSM,
compared with the proposed FLBFH method.

VI. CONCLUSION

The Fog computing environment is highly dynamic in terms
of available resources in the devices and the chances of failure
are very high. This research contributes to minimising the
total number of application failures due to the failure of the
resources; it helps to improve delay and processing time by
proposing a Fuzzy-logic-based failure handling method. The
proposed failure handling method was evaluated using real
failure traces from LANL. Compared with the existing failure
handling approaches, we found an improvement in average
delay and total processing time which were 56% and 48% respectively on average. For future work, we will consider
the implementation and evaluation of the proposed method in
the real Fog computing environment, as well as power-aware
resource allocation. The proposed method can be improved
further by selecting more appropriate Fog devices which have
less chance of failure.

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