International Journal of Computer Engineering & Technology (IJCET)
Volume 9, Issue 5, September-October 2018, pp. 96–108, Article ID: IJCET_09_05_013
Available online at
http://www.iaeme.com/ijcet/issues.asp?JType=IJCET&VType=9&IType=5
Journal Impact Factor (2016): 9.3590(Calculated by GISI) www.jifactor.com
ISSN Print: 0976-6367 and ISSN Online: 0976–6375

RESOURCE ALLOCATION PLANNER FOR DISASTER RECOVERY (RAP-DR) BASED ON PREEMINENT RESPONSIVE RESOURCE ALLOCATION USING PARAMETER SELECTION OF VIRTUAL MACHINES OR CLOUD DATA SERVER

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ABSTRACT

Off-site information protection such as replicating critical information to a physically remote site is maybe the most major technique to guarantee fault-tolerance and empower disaster recovery. In this paper present RAP-DR: a Resource Allocation Planner for Disaster Recovery. RAP-DR gives an ideal method for recovering critical business data into Data Centers (DC's) over a few Geographic areas based on the Preeminent Responsive Resource Allocation using Parameter Selection(PRRAPS) approach utilizing Feature (Parameter) Selection Methods. The main objective of this method is to achieve the utilization of the node while allocating the resources. Thus to construct an optimized resource allocation model by enhancing the IGTRAP of the adaptive resource allocation system with the parameter selection is designed. The enhanced IGTRAP-PRRAPS is employed, to attain the optimized resource allocation scheme that determines the optimal virtual machine to achieve the resource effectively hence, it reduce the resource allocation time.

Key words: Resource Allocation Planner, Resource Attribute Selection, Disaster Recovery, Preeminent Responsive Resource Selection, Recovery Data, Parameter Selection.

Cite this Article: A. Punitha and Dr. Nancy Jasmine Goldena, Resource Allocation Planner for Disaster Recovery (RAP-DR) Based on Preeminent Responsive Resource Allocation Using Parameter Selection of Virtual Machines or Cloud Data Server. *International Journal of Computer Engineering and Technology,* 9(5), 2018, pp. 96-108.
http://www.iaeme.com/IJCET/issues.asp?JType=IJCET&VType=9&IType=5

1. INTRODUCTION

Business continuity is vital necessities of many businesses, as a sudden service disruption can specifically impact business goals causing huge losses in terms of revenue, business reputation and losses of market share.

Indeed, a few organizations may find that it's hard to survive a serious disaster [12]. The reasons for disasters can either be unintended events, for example, a power failure or intentional, for example, a denial of service attacks. Consequently, an organization must have a disaster recovery plan (DRP) which is executable, testable, adaptable and maintainable. Such a plan must fulfill cost constraints while accomplishing the target recovery objectives; that is, recuperation time objective (RTO) and recuperation point objective (RPO) [1].

Many smaller organizations may think that it's hard to afford the desirable disaster recovery plans. Henceforth, some may have just only periodic data backups. This is because of the way that traditional disaster recovery plans regularly rely upon having two identical sites: an primary and an auxiliary site, which might be situated at some distance. Unfortunately, having two sites will add essentially to IT cost for a disaster that is probably to happen only rarely and therefore may appear unjustified overhead. This may clarify why around 40-50% of small businesses have no DRP and no current future tentative to have one [2].

Modern day datasets are exceptionally rich in data with information gathered from a millions of sites, blogs with valuable data. This makes the data high dimensional and it is very normal to see datasets with several features and isn't irregular to see it go to many thousands. Feature selection is additionally called variable selection or attributes selection. It is the automatic selection of attributes in the data (such as columns in tabular data) that are most relevant to the predictive modeling issues that are working on.

Feature selection is unique from dimensionality reduction. The two techniques look to reduce the quantity of attributes in the dataset, however a dimensionality reduction method do as such by making new combinations of attributes, where as feature selection methods incorporate and avoid attributes present in the data without changing them. Feature selection techniques can be utilized to identify and evacuate unneeded, insignificant and redundant attributes from data that do not contribute accuracy of a predictive -model or may in fact diminish the accuracy of the model.

2. REVIEW OF LITERATURE

A disaster recovery plan sounds like a complex business report, but it can be as simple as planning ahead to stay away from issues and being set up in the event a issue happens. This kind of planning won't just help in case of a catastrophic failure, like a fire, but also in more mundane situations, like an employee accidentally overwriting a critical record.

The iSCSI protocol [3], a SAN protocol based on TCP/IP, may turn into an option in alternative to FC. iSCSI transports SCSI commands, normally issued to specifically attached disks, over TCP/IP connections, to allow access from/to remote devices which can be in the end on the Web extending SAN's borders out of data center's network. In any case, packet losses, retransmissions and large latencies may happen when managing IP best effort service.

Wiboonratr and Kosavisutte have dealt on optimizing DRP's as they recommend dividing systems into little components with different criticality levels and by prioritizing basic parts of a framework over less critical components [4]. Now, there is sufficient field knowledge to allow formulation of analytical models. Alhazmi [5] designed and implemented a software tool that can copy Calamity Disaster Recovery planning systems and help designers to design, optimize and test the outline before physical implementation. The tool takes input data identified with recovery and demonstrates the trade-off between the Recovery Time Objective, Recovery Point Objective and the Cost.

Wood et al. [6] in their investigation analyzed and proposed cloud based model for the Disaster Recovery solution. The creators argued that the cloud based model is much improved than the committed recovery model. The cost of the cloud based disaster recovery model is significantly not as much as the dedicated recovery model. There were cost decreases to the tune of 80%.

3. BACKGROUND AND LIMITATION OF THE EXISTING SYSTEM

The background study portrays the disaster recovery composes as following to decide the technique for recovering from outage.

In Type-I, there is no arrangement for back-up or recuperation site. There is no documentation; no back-up equipment is arranged, no emergency plan. The recovery time objective is erratic. Total recovery of the systems isn't conceivable. There is no cost necessity in this tier. In Type-II, data from the essential site is transported to the offsite area utilizing private truck get to technique (PTAM). There is no hot site. Amid the disaster situation, the information is recovered from the offsite and the recovery location needs to be determined. The recovery time for this type is over couple of weeks. In Type-III, the conventional method for storage of information, tapes is supplanted by the disks. In this type the auxiliary site is active. There is a constant transmission of information between the primary and auxiliary locales. Both the sites have the duplicates of critical data. For non critical data, transmission utilizing PTAM is as yet accessible. In Type-IV, the information between the primary and secondary sites is synchronized by remote two phase commit procedure. Just the in flight information is lost amid the disaster. The recovery time objective is typically twelve hours. In type-V, the primary and auxiliary sites are synchronized with a high bandwidth. Advanced coupling and clustering software is utilized in order to synchronize the information. The tier makes utilization of automatic switching to switch between primary and auxiliary site. The recovery time objective is few minutes.

Traditionally, the data backup and archival are done utilizing magnetic tapes which are processed and transported to a remote area. However, such procedure is manual, awkward and rapid data restoration and service resumption is often not possible. Recently, with the appearance of cheap, improved storage and online disk backup technology, and advances in networking; online remote backup options have become attractive. The storage area network and virtualization technology has turned out to be sufficiently enough to make a storage volume snapshot to a remote site.

4. NEED OF FEATURE SELECTION IN RESOURCE ALLOCATION

Machine Learning gives intends to obviously investigate massive amounts of information and therefore to: determine different ends, make recognition for concealed information, discover patterns inside the information and so forth. As learning depends on the accessible information, its preprocessing is essential to such degree that more often than not of the task may be spent for this stage. Throughout information processing different issues of the information can be tended to: feature modeling and development, data normalization, and data transformation. Various learning algorithms, for example, neural systems, Naive Bayes, decision trees prominently encounter corrupting execution when the datasets contain excess or irrelevant features. This wonder is affirmed with hypothetical and observational proof in a lot of research papers. The issue of feature selection can be characterized as the undertaking of determination of subset includes that portray the speculation in any event and additionally the first set.

The interpretation of information illustrations is enhanced with include features, which in turn can prompt:

- Machine learning algorithm's performance aspects are improving.
- Reducing the training and execution times of techniques.
- Enhancing the memory necessities and permit use of more algorithms.
- Enhanced strength to over-fitting.
- Better perceptive and representation of the information.

Various techniques for feature selection focus on different parts of the above objectives, or accomplish similar objectives yet in various ways.

5. PROPOSED SCHEME

This work exploits advantage of feature selection techniques to solve the issue of resource allocation and proposes a new model to improve the result of resource selection process.

A. Data Center

Cloud computing is developing as new and modern day computing technique in the present datacenters different heterogeneous resources, platforms, or software are provisioned on clouds through web. The clients can ask for the resources of the cloud whenever amid their operation. The client's applications kept running on virtual machines (VM) determined for them. Based on the necessities of the application running on the VM, the cloud administrator should provide suitable resources for VM. Different sorts of utilizations running at the same time on cloud have distinctive resource prerequisites. Along these lines, allocating enough and suitable assets to VMs is a challenging issue for resource manager. Virtualization innovation which is the premise of cloud computing encourages the way toward sharing physical machines' (PMs) resources between VMs. Thus, the resource manager aggregates all the accessible resources and enhances the resource utilization.

B. Parameter Vector

Frequently resource management tools consider about CPU, RAM, and disk parameters. In spite of alternate techniques, this paper considers every one of the parameters which are vital in resource allocation. Moreover, this work takes the significance of parameters into consideration. The parameters are stored as a vector and it's depicted as follows:

Fragments

Fragmentation is a procedure which cuts sensitive record into a few fragments so that it is difficult to accomplish total record in one attempt, and for every registered client a secret key is created so that to secure the data.

Total Disk Size

It demonstrates the number of disk and its disk size in the resource machine.

Response Time

It deals with the response time according to the request.

Transfer Rate

It demonstrates the transfer width on every connection based on bandwidth.

Count of Failures

It quantifies the failures during client accessing or reply over transaction.

RTO

The **recovery time objective** (RTO) is the targeted duration of **time** between the occasion of failure and the point where operations continue.

RPO

A **recovery point objective** (RPO) is the maximum length of time permitted that information can be restored from, which might possibly mean data loss. It is the age of the documents or information in backup storage required to resume normal operations if a computer system or network failure occurs.

Replication Latency

Data replication implies keeping a number of replicas on the same server on dissimilar servers. It demonstrates the latency over the replication.

Utilization Rate

CPU utilize can be checked through VMware or through the VM's operating system. Usage should generally be <= 80% on average, and > 90% should trigger an alarm, yet this will change depending upon the applications running in the VM.

Rate of QoS

Quality of service(QoS) is the depiction or estimation of the overall performance of a service, for example, a telephony or computer network organize or a cloud computing service, especially the performance seen by the clients of the network. To quantitatively measure quality of service, a few related parts of the network service are frequently often considered. For example a packet loss, bit rate, throughputs, transmission delay, availability, jitter, and so on.

Count of Attack

It demonstrates the numeric esteem which is stored count the value of attack was happened.

Quantum Time

It is one of the response time estimation which divides the response time in one forth.

C. Feature (Parameter) Selection

In machine learning, feature selection, otherwise called attribute selection, is the way toward choosing a subset of relevant attributes in historical data to shape feature vector for building predictive models. The selection of a suitable feature vector is critical because of the phenomenon known as "the curse of dimensionality ". That is, each dimension that is added to the feature vector requires exponentially increasing data in the training set, which more often than not results in practical significant performance degradation. Consequently, it is important to find a low dimension of feature vectors that catches the essence of resource allocation in practical situations. In order to decrease the dimensionality of feature vectors, just valuable data for the resource allocation can be chosen as features.

As the time-invariant parameters keep unchanged, in order to limit the dimension of the feature vectors, just the time-variation parameters can be thought to be features. Also, some time-variation parameters can't be chosen as features since it might be excess within the presence of another significant feature with which it is strongly associated.

5.1. Firefly Algorithm

Nature inspired procedures are all the more powerful for optimization issues. This paper introduces a novel methodology for dimensionality reduction based on firefly calculation (FA). Firefly calculation (FA) [8] is encouraged by biochemical and social parts of actual fireflies. Actual fireflies create a short and rhythmic flash that causes them in communicating in their mating partners and furthermore serves in as protective warning mechanism.

FA details this flashing behavior with the objective function of the issue to be optimized. The subsequent three rules are idealized for essential formulation of FA

(1) All fireflies are unisex so fireflies will attract in one another regardless of their sex.

(2) Attractiveness is relative to their brightness, which diminishes as distance increases between two flies. Thus the less glow one will shift towards the glower one. In case it is unable to determine glower one it will shift randomly.

(3) The brightness of a firefly is resolute by the landscape of the objective function.

The following describes the basic FA algorithm.

Algorithm FIRE_FLY

```
{
    Objective function f(x),x=(x1,......x)T
    produce initial population of fireflies xi (i=1,2,...n)
    Light power Ii at xi is determined by f(xi)
    describe light absorption coefficient γ
    While(t>MaxGeneration)
    for i=1:n all n fireflies
    for j=1:i all n fireflies
    if (Ij>Ii), shift firefly i towards j in d-dimension;
    end if
    Attractiveness diverges with distance r via exp[-γr]
    estimate new solution and renew light intensity
    end for j
    end for i
    Rank the fireflies and seek the current best
    end while
    Post process outcomes and visualization
}
```

The essential FA accept there exists ‘n’ fireflies x_i, i=1,2,… .,n at first situated randomly in the space and intensity ‘i’ of every firefly is related with the objective function. Just firefly with higher flash intensity pulls in the other one i.e. $I_i>I_j$, j=1,2,…n, j≠i. Attractiveness or the brightness of firefly differs with the distance between firefly i and firefly j i.e. $r_{ij} = d(x_i,x_j)$. Furthermore the intensity I diminish with the distance from its source and it is also absorbed in the air. Thus most of the fireflies are noticeable only to a restricted distance.

5.2. Relief

The Relief algorithm was first depicted by Kira and Rendell [KIRA92] as a simple, fast, and efficient approach to attribute weighting. The yield of the Relief algorithm is a weight between −1 and 1 for each attribute, with more positive weights indicating more prescient attributes. An example is chosen from the data, and the closest neighboring sample that belongs to the same class (nearest hit) and the nearest neighboring sample that belongs to the opposite class (nearest miss) are identified. An adjustment in attribute value joined by a change in class leads up to weighting of the attribute based on the intuition that the attribute change could be responsible for the class change.

On the other hand, a adjustment in attribute value accompanied by no adjustment in class leads to down characteristic of the attribute based on the observation that the attribute change had no impact on the class. This technique of updating the weight of the attribute is performed for a random set of samples in the data or for every sample in the data. The weight updates are then averaged so that the absolute weight is in the range [−1, 1]. The attribute weight computed by Relief has a probabilistic analysis. It is relative to the difference among two conditional probabilities, explicitly, the probability of the attribute's value being various conditioned on the given nearest miss and nearest hit correspondingly.

As outlined by the pseudo-code in Algorithm, the Relief algorithm cycles through m random training instances (R_i), selected without substitution, where m is a user-defined parameter. Each cycle, R_i is the 'target' instance and the feature score vector W is updated.

Algorithm RELIEF

{

Input: n=number of training instances

a=number of attributes

Output: m=number of random training instances out of n used to update W

1: initialize all feature weights W[A] := 0.0
2: for i:=1 to m do randomly select a 'target' instance R_i
3: find a nearest hit 'H'
4: find nearest miss 'M' (instances)
5: for A:= 1 to a do
6: W[A] := W[A]−diff (A, R_i , H)/m+diff (A, R_i , M)/m
7: end for
8: end for
9: return the vector W of feature scores that estimate the quality of features

}

Relief recognizes two closest neighbor instances of the target; one with the similar class, called the nearest hit (H) and the other with the contrary class, called the nearest miss (M). The last step of the cycle updates the weight of a feature A in W if the feature value varies between the target instance R_i and either the nearest hit H or the nearest miss M. Features that have a different value between R_i and M support the theory that they are informative of result, so the quality estimation W[A] is increased. Conversely, features with differences between R_i and H provide confirmation to the contrary, so the quality estimation W[A] is diminished. The diff function in Algorithm calculates the difference in value of feature A between two instances I_1 and I_2, where $I_1 = R_i$ and I_2 is either H or M, when performing weight updates.

5.3. Cuckoo Optimization Algorithm

The parasite behavior of a few types of Cuckoo is extremely fascinating. These birds creatures can set out their eggs in a host nests, and mimic external characteristics of host eggs, for example, color and spots.. In case of this procedure is unsuccessful, the host can throw the cuckoo's egg away or just abandon its nest, making another one in somewhere else. Based on this context, Yang and Deb [13] have built up a novel evolutionary optimization algorithm named as Cuckoo Optimization Algorithm (COA), and they have summarized COA utilizing three rules, as takes after:

- Only one egg at once is laid by cuckoo. Cuckoo dumps its egg in a randomly picked nest.
- The number of available host nests is settled, and nests with high quality of eggs will persist to the next generations.
- In instance of a host discovered creature found the cuckoo egg, it can discard the egg or surrender the nest, and fabricate a totally new nest.

In this segment, the BCOA channel based feature selection methodology is proposed, where the entropy and mutual information are connected to compute the relevance and redundancy in the feature selected subsets. Mutual information is characterized as the data shared between two random variables, which can be utilized in feature selection to assess the relevance among features and class labels. Nonetheless, in feature selection, as a result of the interactions between features, the combination of m exclusively good features may not be the best combination of m features. In this way, it is important to lessen the redundancy among features and select a subset of features with minimal redundancy to one another and maximal relevance to class labels. Hence, both relevance and redundancy are incorporated into the fitness function to control BCOA to search for the best feature subset, which can be spoken to by the algorithm.

Algorithm BCOA

{

begin
split Dataset into a Training set and a Test set;
initialize the population of n host nests x_i (i=1, 2, 3…n);
while (t < Max Generation or stop Criterion) do;
move a cuckoo randomly via Levy flights;
calculate its fitness according to equation 9 on training set;
randomly pick nest along with ‘n’ available nests ;
If ($Fitness_j > Fitness_i$)
substitute j by the new solution
End if
discard a fraction ( ) of poorer nests
construct new ones at new locations using equations 1and 2;
keep the best solution;
level the solutions and seek the recent best;
end while;
compute discrete values consistent with equation 3, 4;
evaluate the classification accuracy of the chosen feature subset on the test set;
return the training and test classification accuracies;
end

}

The proposed algorithm demonstrates the pseudo-code of using BCOA evaluation for feature selection. The portrayal of a cuckoo in BCOA is an ‘n-bit’ binary string, where’ n’ is the number of available features in dataset and furthermore the dimensionality of the search space. In the binary string “1” represents that the feature is selected and “0” generally.

5.4 Preeminent Responsive Resource Allocation using Parameter Selection (PRRAPS)

In cloud computing environment all the resource are sharing by utilizing the virtualization innovation, hence the resources are depicted to as virtual machines and each virtual machine has a restricted limits, for instance processing power, memory size and system transfer speed .The speed of each virtual machine is ascertained in millions regulation for every seconds, work has preparing necessity acquired as far as millions directions.

In this paper, a proposed feature selection strategy Preeminent Responsive Resource Allocation using Parameter Selection (PRRAPS)is acquainted with allocates the resources in an effective way. The proposed methodology PRRAPS is a combination of Correlation based Feature Selection with Crow Search Algorithm. The key objective of this strategy is to search for the accessibility of the resources and allocate the undertaking for the virtual machines. The PRRAPS has their particular focal points while unraveling different issues. In this methodology the individual features of the algorithms are consolidated to display a novel hybrid algorithm to enhance the resource allotment scheme.

The virtual machine is get together with gathering of nodes utilizing correlation based selection, the fitness value is assessed based on the capacity of the virtual machine, and data transfer speedbased on the function computed the P_{best} virtual machine is evaluated and in the following emphasis if fitness function is discovered superior to anything the past fitness value, displace the newer one as P_{best} lastly the best fitness value in the populace is considered as g_{best}. The procedure of crow search through that brings the optimal selection of the accessible virtual machine with ability for the resource distributed. The algorithm for the proposed PRRAPS is given below:

Algorithm PRRAPS

{

Input: J-Job List

Output: V_{Opt} –Virtual machine for optimized resource allocation

Initialize the random number n of virtual machine VM.

For each i= 1 to n

{

For each j= 1 to n

{

Fetch (vm_i,$vm_j \in$ VM)

Evaluate Bandwidth(vm_i,vm_j) and Capacity(vm_i,vm_j)

If (vm_i> vm_j)

{

Gather Correlated VM from the list

VM_{List} = GetPopulation(vm_i)

}

}

}

For each i= 1 to m from VM_{List}

{

Compute Fitness (vm_i)

If (Fitness (vm_i) $<$ P_{best-i})

{

$P_{best} = vm_i$

}

Else

{

Choose next vm_i

}

Update P_{best}

}

g_{best} = evaluate best fitness value of P_{best}

Select gbest as optimal VM

New position $<$ gbest VM in VM_{List}

If new position of VM in VM_{List} $<$ previous VM in list

{

Elect new position of VM_{List} in optimal VM

Update the position of the virtual machine

Assign resource to virtual machine // for all VM_i.

}

}

At first the collected virtual machine is finished by utilizing correlation based selection among the n number virtual machines. Initiate the number of population in the job and the virtual machine, and after that assess the fitness capacity of each virtual machine by utilizing the crow search. The fitness value is computed by the data transfer speed and the limit of the virtual machine and for the resource, with the minimum execution time and deadline are acquired. The best fitness value is picked as the g_{best} virtual machine and after that allocates the resource to the optimal virtual machine.

6. PERFORMANCE EVALUATION

This section illustrates the performance evaluation for the features selection for the resource allocation during the natural disasters. In this paper, the feature selection algorithms are examined for the evaluation of performance metrics that takes for the better allocation of resources.

Table 1 Performance Evaluation for Feature Selection Techniques

Methodologies	Accuracy Ratio (%)	F-Measure
Firefly	86.28	0.6271
Relief	81.43	0.3987
BCOA	92.30	0.8235
PRRAPS	95.22	0.8987

The performance evaluation for various feature selection techniques is depicted in Table 2. The table illustrates the evaluation of performance metrics such as Accuracy Ratio and F-Measure that shows that the proposed method PRRAPS provides better accuracy and F-Measure for resource allocation using feature selection.

Table 2 Selected Features using Feature Selection Techniques

Methodologies	Selected Features
Firefly	ii , iii , v, vii, x
Relief	i , ii, x, viii, iv
BCOA	i, ii, xii, x, iv
PRRAPS	xi , xii, ix, vi, iv

6.1. Accuracy Ratio

Accuracy Ratio (AR) is an outline quantitative measure of the performance in classification model. The AR measure expresses the ratio of the area above and under the power curve of the model under consideration versus the “perfectly " discriminating model.

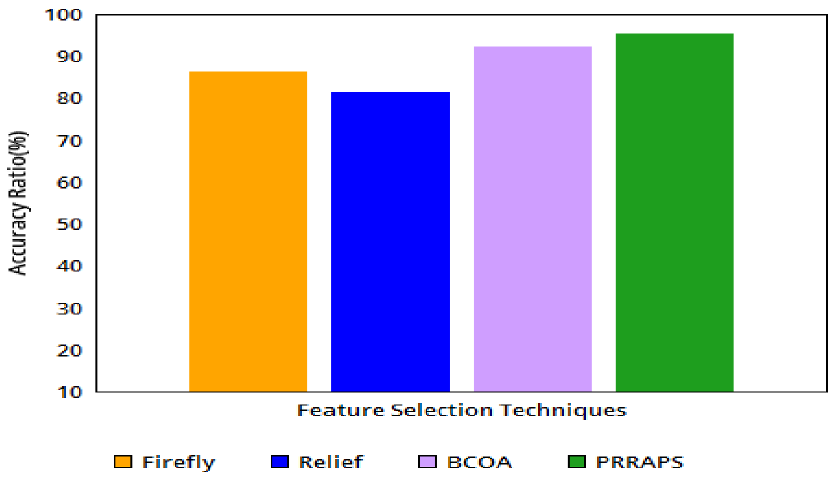

Figure 1 Accuracy Ratio for Various Feature Selection Methodologies

Figure 1 illustrates the accuracy ratio evaluation for the proposed feature selection techniques with other methodologies. The figure depicts that the proposed PRRAPS provides good accuracy result while resource allocation.

6.2. F-Measure

F1 Measure is the weighted average of Precision and Recall. In this manner, this score considers both false positives and false negatives. Instinctively it isn't as easy to understand accuracy, yet F1 is usually more helpful than accuracy, especially have an uneven class distribution.

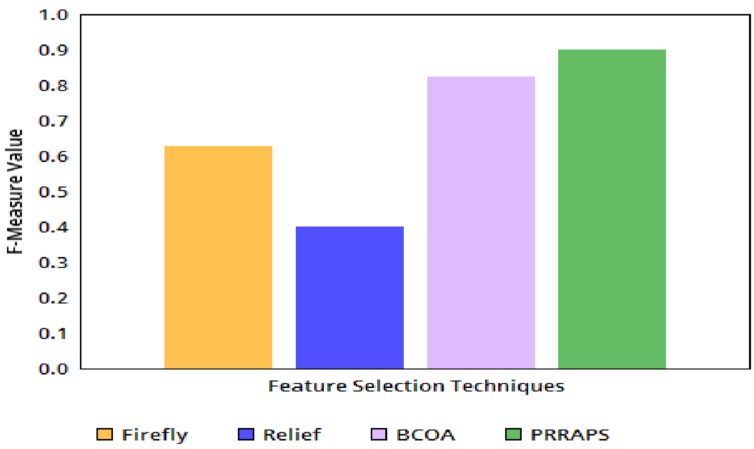

Figure 2 F-Measure Evaluation for Feature Selection Techniques

The harmonic mean value computation is shown in Figure 2. The harmonic mean or F-measure computation gives high value for the proposed feature selection method than the other methods.

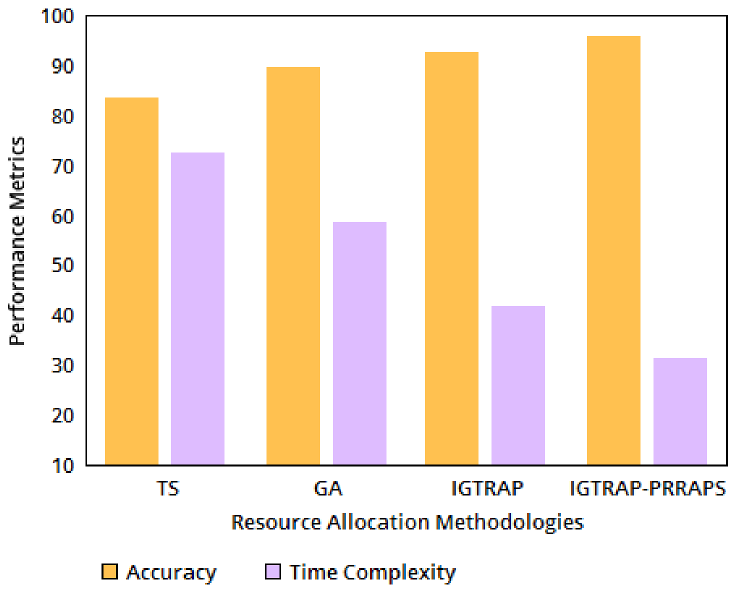

Figure 3 Performance Evaluation for Resource Allocation Systems

Figure 3 depicts the performance evaluation for the resource allocation systems. The figure describes that the proposed system of IGTRAP-PRRAPS using Feature selection method for resource allocation provides good accuracy ratio and less in time complexity than the resource allocation systems Tabu Search(TS), Genetic Algorithm (GA) and IGTRAP [9].

7. CONCLUSION AND FUTURE ENHANCEMENT

Disaster Recovery Planning is a one of the amongst the most critical areas that require thorough efforts from practitioners as an unforeseen occasion can convey the everyday tasks of an enterprise to a grinding halt. The parameters recognized in this paper are interrelated and acquires complexity in the decision making process for choosing the optimum disaster recovery strategy. In future research forwarded to examine a few key issues including effective collection of cross datacenter resources, load-balancing optimization for fine-grain hubs on each machine, quick development of Virtual Cloud as well as container performance improvement.

REFERENCES

[1] T. Wood, E Cecchet, K. K. Ramakrishnan, P. Shenoy, J. van der Merwe, and A. Venkataramani, “ Disaster recovery as a cloud service: economic benefits & deployment challenges”, Proc. 2nd USENIX Conference on Hot topics in cloud computing (HotCloud'10), Berkeley, CA, USA, 2010, pp. 8-8.

[2] Survey Indicates Half of SMBs Have No Disaster Recovery Plan, Chris Preimesberger, September 2009, http://www.eweek.com/c/a/Data-Storage/SurveyIndicates-Half-of-SMBs-Have-No-Disaster-RecoveryPlan-687524

[3] IETF, RFC 3720 (iSCSI), April 2004

[4] MontriWiboonratr and KittiKosavisutte, “Optimal strategic decision for disaster recovery,” Int. Journal of Management Science and Engineering Management, Vol. 4 (2009) No. 4, pp. 260-269.

[5] Alhazmi, O.H. (2015), Computer Aided Disaster Recovery Planning Tools (CADRP), International Journal of Computer Science & Security (IJCSS), 9(3), 132-139.

[6] Wood, T., Cecchet, E., & Ramakrishnan, K. K. (2010). Disaster recovery as a cloud service: Economic benefits & deployment challenges. 2nd USENIX Workshop on Hot Topics in Cloud Computing, 1-7.

[7] Seven Tiers of Disaster Recovery. Online Retrieved From https://en.wikipedia.org/wiki/Seven_tiers_of_disaster_recovery

[8] Yang, X., (2009), ‘Firefly Algorithm for Multimodal Optimization’, SAGA 2009, LNCS 5792, pp.169-178, 2009]

[9] A.Punitha, Dr. Nancy Jasmine Goldana, Adaptive Resource allocation in Disaster Response using Best Resource Reserve (BRR) Approach , International Journal of Emerging Technologies and Innovative Research(JETIR)

[10] R. T. Marler, J. S. Arora, Survey of multi-objective optimization methods for engineering, Journal of Structural and Multidisciplinary Optimization, Volume 26, Number 6, Pages 369-395, April 2004.

[11] C.M. Gauger, M. Kohn, S. Gunreben, D. Sass, S. Gil Perez, ¨ Modeling and Performance Evaluation of iSCSI Storage Area Networks over TCP/IPbased MAN and WAN networks, Broadnets 2005, Oct. 2005

[12] Disaster Recovery for Small Business, Technical White Paper, Iomega Corporation, March 18, 2009