https://doi.org/10.46335/IJIES.2021.6.3.3 **e-ISSN: 2456-3463**
Vol. 6, No. 3, 2021, PP. 10-15

International Journal of Innovations in Engineering and Science, www.ijies.net

Network and Service Anomaly Detection in Multi-Service Transaction-based Electronic Commerce Wide Area Networks

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***Received on**: 25 April, 2021, **Revised on**: 20 May, 2021, **Published on**: 22 May, 2021*

Abstract - *The effective detection of network failures and operational malfunctions is the key to quick recovery and thus strong communication. In this paper we present the methods and algorithms we have developed with the aim of improving the effective and flexible acquisition of network service malfunction (failure and operational corruption) on transaction-based Electronic Commerce Wide Area Networks (WANs). Specifically our approach to detecting critical network access detects network malfunction and failure in many service networks, where the performance of service classes is equally dependent and highly interconnected, and where external or natural resources (e.g. unmanaged or unmanaged equipment within a customer) can have significant impact on network performance and performance. In this paper we define and use algorithms (1) to sample and convert raw material records into operational data support services that highlight non-network coverage, (2) creates flexible operating parameters and service level for real-time network detection and service inconsistencies, and (3) enables real-time network anomaly detection.*

I- INTRODUCTION

Active detection of network failure and inefficiency is key to faster and thus stronger connections, and gaining increasing attention recently[1,2]. Error detection should be automatically adjusted, if possible, to changing variables and network smuggling methods. This applies especially to the current communications infrastructure, where both the transition and the route change and change at a very different time scale. Network error detection is one of the few "active" error detection methods available to detect network errors automatically. Anomaly Discovery aims to address the presence of network errors by detecting potential performance impairment in these networks and their applications. This is achieved through algorithmic recognition of network failures and improper use of resources. The key says
to detect this decrease in performance, and by inserting the errors themselves, before the failure of the service level and compromise. In this way, unfavorable network detection can detect network errors in a timely manner, and service level failures are expected. The error detection is usually related to the detection of soft and complex network errors. This paper focuses on the detection of mild errors, as opposed to "heavy" alarms / failures [3,4,5], of networks and their devices for the following reasons. (1) They occur more frequently than the most serious errors. (2) Soft errors affect the QoS (service quality) of network applications and services, which need to be maintained in real time. (3) By obtaining soft errors at a high level the failure of the level and level of service and collapse can be expected and thus avoided in advance (effective error detection). (4) Detection of serious errors such as disconnection and power failure in general designed as alarms raps for device components manufacturers, which detect and detect error programs such as alarm assembly systems [6,7].
As communication infrastructure evolves into multiple multi-service networks, the allocation of network resources across multiple services classes strengthens the performance of all classes supported on reasonably differentiated networks (Figure l). Therefore, performance reductions in one set of service classes may adversely affect the performance of others. This

https://doi.org/10.46335/IJIES.2021.6.3.3 e-ISSN: 2456-3463
Vol. 6, No. 3, 2021, PP. 10-15

requires unusual detection of network and service errors. Finally, faulty items outside the control of network monitoring systems can also undermine the performance of a well-monitored network (Figure l).

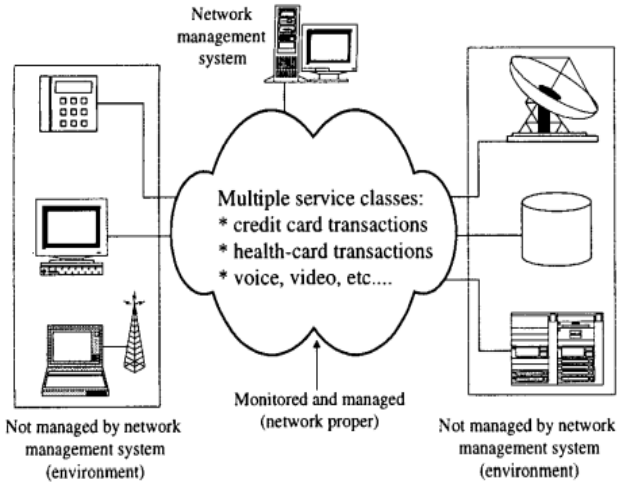

Fig 1- A managed multiple service class WAN and its environment (i.e., non-monitored parts)

II-NETWORK ANOMALY DISCOVERY: SUMMARY

At this stage, consistent network acquisition of the network is summarized as a three-step process. First, sample transaction network data to highlight the potential confusion of network service per service category. Second, the temporary operating parameters of service classes are built from historical network data for operational features. Third, invalid detection is made by comparing real-time sample data with baseline data. Specifically the three steps for the detection of variable network anonymity are:

1. Real Estate Selection of Transaction Record Options

This algorithm generates network samples (e.g., transaction records generated by network switches) to detect transactlOns with a high probability of being unpopular, depending on the sample strategy based on the historical performance of the service category in question. The typical design of a faulty detection system is shown in Figure 2, which highlights its three main functional components: the sample, the generator (or limit) of the generator, and the anonymous detector. In this system, network performance data is accumulated online by the sample for analysis. The sample does not include performance measures (e.g., traffic volume, or circuit usage, from service classes in a transaction-focused network) in which undesirable data is highlighted. The performance output of historical network data by the sampler is analyzed by the process maker to create flexible and dynamic performance parameters (e.g., Temporally temporally). The detector compares the output of real-time network performance data by sample with operating limits and the predictable error detection method. Detector results are usually sent to the user graphic interface (GUI) to notify network operators of network irregularities and errors, or are sent directly to network control modules for automatic response and control (e.g., circuit breaker, module rerouting, etc. the balance between sample frequency and performance correction.

2. Temporul-based Performance Thresholds

Using the network operational standard, each service threshold can be divided into 4 lntO classes: weekdays, Saturdays, Sundays and holidays. Service class history details are used to create these flexible routes for each service. Expected performance of services predicts that these limits will increase.

3. Anomaly Discovery

Expected service performance is predicted by the above parameters, and deviations (in all sizes and dimensions, as defined by the set of error process) from expectations are indicators of network service malfunctions.

The typical structure of a faulty acquisition system is shown in Figure 2, which highlights its three main functional elements: sample, rule (or limit) a generator, and a faulty detector. In this system, network performance data is accumulated online by the sample for analysis. The sample excludes performance measures (e.g., traffic capacity, or circuit usage, from service classes in a transaction-focused network) in which undesirable data is highlighted. The output of the sample performance network data is analyzed by the process maker to create flexible and dynamic performance thresholds (e.g., temporary). The detector compares the output of real-time network performance data by sample with operating limits and the predictable error detection method. The results of the detector are sent to the user interface (CUI) to notify network operators of network irregularities and errors, or to be sent directly to create network control modules with feedback and automatic control (e.g., circuit breaker, redirect module, etc.).

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Vol. 6, No. 3, 2021, PP. 10-15

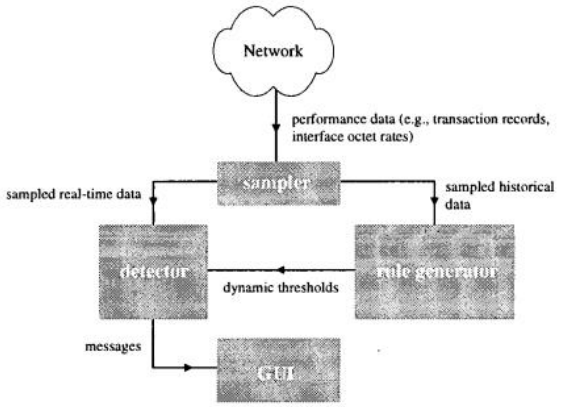

Figure 2. Generic architecture of a network anomaly detection system.

III-PERFORMANCE OF TRANSACTION-BASED TRADING NETWORKS BASED ON TRANSACTION

At this stage, the implementation of the generic transaction-based Electronic Commerce WAN phase was introduced and analyzed. The analysis is based on structure
of flexible algorithms for detecting non-network service (described in Section 4). Updated network data is collected from the AT&T Transaction Access Service (TAS) network. Typically, Transaction-based Electronic Commerce networks are datdtelecom (or a combination of both) networks that use transactions that take a short time (seconds) between a set of terminals (e.g., credit card scanners, or personal computers) and a set of processing servers (e.g. e.g. credit processing servers). For example, transactions between credit cards scanned at merchant locations and processing servers at credit processing centers are conducted by this type of network. These transactional networks deliver network management and operational data ranging from MIB-I1 data to network alarms. In a transaction split, the following 4-Tuple variants indicate transactions:
(i9 s, t ,, Y At ,,,)
where
• "s" means the identifier of the active service category
I "i" means the active identifier,
it belongs to them,
, T ,, means the start time of the transaction, and
• In ,, means the transaction time (for each service phase, Af, s have intermediate, upper and lower quartiles, and the opportunity to distribute opportunities).
Activity identifier separately identifies activity (e.g., it can be a positive number counter as transactions appear on the network). Service class identifier identifies the service item. For example, credit card transactions and health-related transactions (e.g., drug replenishment order) are two distinct categories of transactions. Different service classes (in the standard network of multi-service classes, the number of service classes of about ten or even hundreds), each has a longer transaction time than the other. Legally, each component of the in-service service has its own transaction time, its upper and lower quartile, and its distribution-time function. Finally, the start time of a transaction indicates the start of the transaction and its duration indicates how long it lasts, as the names imply. A WAN-focused production transaction can support tens or even hundreds of transaction service classes in the same infrastructure, making it a set of visual networks that are logically segmented (but highly functional) in relation to each service segment. A detailed examination of the transaction statistics structures and their service categories, the allocation of a stand-alone service segment (with a daily transaction volume of about 140,000, and a transaction time of between 5.8 seconds) is illustrated in Figure 3. One of the most important requirements for improving network access and services it is clear that the statistical properties of random visuals (e.g., transactions, traffic intensity, or byte rate values) should not be timely (hence the prediction of the future This visualization should be speculative with respect to the periodic revision of statistical findings, because the pattern is "normal". "Statistics are identified and analyzed as the presence of network problems. As can be seen in Figure 3, PDFs of service phase 1 transaction are repeated ns you are every seven days in a row. This same effect can be clearly seen in Figure 4, which highlights the familiarity of PDFs at box sites. For all service classes in the trading networks used for transactions, this calculation applies normally.

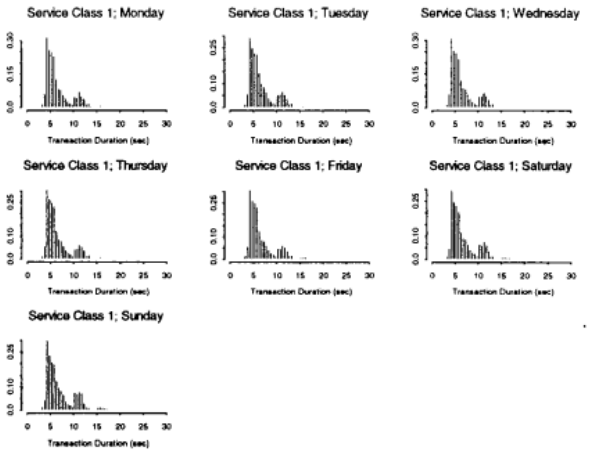

Figure 3. PDFs of transaction duration of service class 1 on 7 consecutive days, showing that they are highly repeatable. All probabilities are normalized.

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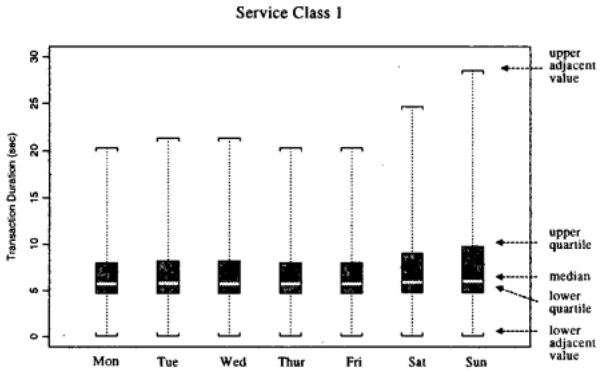

Figure 4. Box-plots of the PDFs from Figure 3.

Random (or visual) variables selected for acquisition that do not match the size of the traffic supported by the service. The amount of traffic can be calculated directly from the transaction period and the initial transaction period. It measures the amount of active transactions assigned to a particular category of service as operating time, depending on the size of the capture interval. Clearly shown in Figure 5, the transaction is represented as arrows in the "arrival diagram" (x-axis time in bzr units, while the y-axis spreads the whole number transaction identifier (see Equation (I)). With this presentation, the arrival times of the artificial are represented as the arches of the artificial arrows, while the length of the tasks is represented as the length of the archer's arrow. Within the capture interval (for length & time), the size of the traffic is equal to the total number of transactions that fall within the barrel, either partial or total. The transaction number is calculated by summarizing all the operations (e.g., arrows) that fall into that barrel, and the traffic force I, r of the service section s during Tn, $ (unit: binning interval Sr, is:

$$I_s(T_{n,s}) = \sum_i \Delta t_{is} \Big/ \delta T_s \Big|_{T=T_{n,s}} ; T_{n,s} = n \times \delta T_s, n = 0,1,\cdots,N_s. \quad (2)$$

For example, of the six transactions presented in Figure 5, the first barrel (O <T1 &) contains 6 transactions which is why 6 units (circuits or Erlangs) of traffic consolidation. In addition, the second barrel (bzr <T12iQJ contains 4 transactions which is why 4 units of solid traffic; and finally, the third barrel (2bzr <T136T) contains 2 transactions and therefore 2 units (circuits or Erlangs) of traffic congestion.

The weekly traffic capacity of service class "1" is shown in Figure 6, generated from PDFs shown in figures 3 and 4. As will be explained in the next section, the capture period is a public transaction function, so that high-potential transactions can be reflected in the size of the traffic.

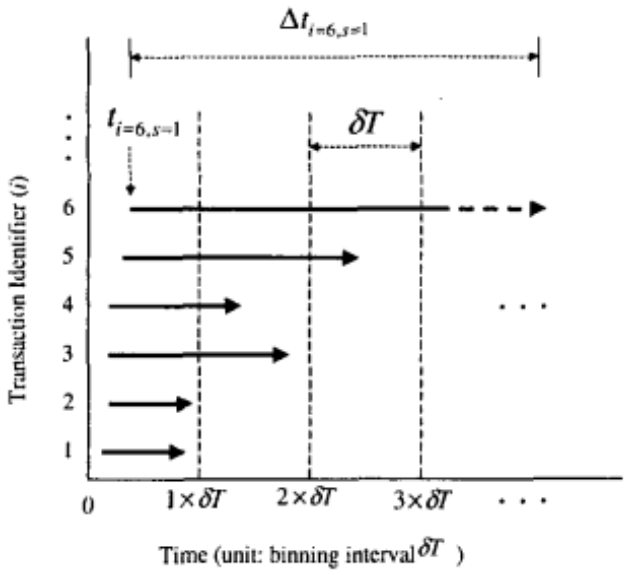

Fig 5- ARRIVAL Diagram of Transactions in Service Class

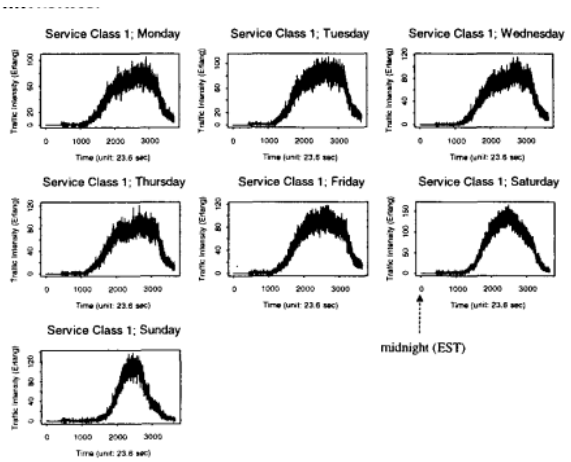

Fig 6- Traffic Intensities of service class 1 Generated from PDF generated from Fig 3 and 4.

IV-IMPLEMENTATION OF ANOMALY DETECTION SYSTEM

Currently, an online anomaly network detection system has been implemented in the AT&T TAS network. The system has three active modules: sample, threshold generator, and detector, in addition to the GUI. The sample analyzes real-time and historical records to produce robust traffic according to each service category. The monitoring network creates transaction records for all transactions in 15 minutes (this is a configurable parameter) daily. The 15-minute data feed creates real-time performance data while daily data feeds are used as the limit data history generation. In any case, each transaction record is managed to display traffic capacity in support of the service. The sample time for each phase of the service is different, flexible,

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and depends on its "medium" historical service time. In the current launch the 15-min data feed is aggressively integrated into the relationships database (Oracle). The sampler receives records from the database to calculate the actual time traffic for all TAS service classes, during sample times for individual service classes. These street power supplies are supplied as a detection detector (will be explained below). On the other hand, daily feeds are stored as flat files, which are analyzed by the sample to produce the historical roadmap for all categories of service. This historical information is included in the threshold generator, which creates powerful limit templates for all service categories (Figure 7).

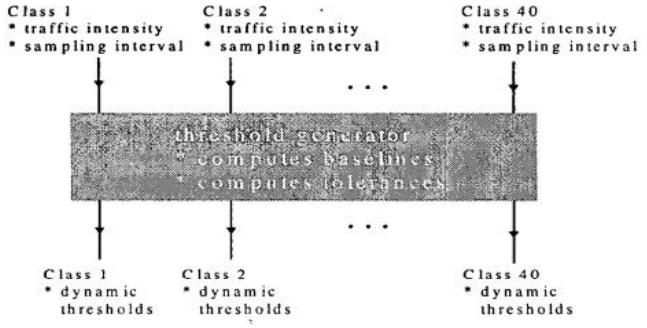

Fig7- The Threshold generator computes dynamic threshold (i.e. Baseline + tolerance)for service class from historical traffic intensities and sampling interval output from sampler

Specifically, for each TAS service, flexible routes are divided into 4 groups: (1) weekdays, (2) Saturdays, (3) Sundays, and (4) holidays. For each 4th limit group, a set of flexible limits is designed to predict the expected performance of TAS services during days, Saturdays, Sundays, and holidays, respectively. Each set of dynamic boundaries (upper and lower threshold) is built on the first predicted base I, (Tn ,,,) and tolerance d, v (Tfl ,,) (note: "-" means "predictor") as follows

$$\text{upper\_threshold} = \tilde{I}_s(T_{n,s}) + 2\tilde{\sigma}_s(T_{n,s}) \Big\}^{wkdys}_{sats\ suns\ holiday} \quad (3)$$

$$\text{baseline} = \tilde{I}_s(T_{n,s}) \Big\}^{wkdys}_{sats\ suns\ holiday} \quad (4)$$

$$\text{lower\_threshold} = \tilde{I}_s(T_{n,s}) - 2\tilde{\sigma}_s(T_{n,s}) \Big\}^{wkdys}_{sats\ suns\ holiday} \quad (5)$$

Basics 1, (Tn ,,) and 8 tolerance, (Tn, s) are calculated from historical transaction data by analysis of the one-time series and included on the day "day", "Saturday", "Sunday" and "holidays". "Classes. The [y (T ,, s) represent the "estimated" power of the service levels, while the (T ,,, s) represent the "average" power of the corresponding street force. Both 7, (T ,,, $) s and 8, (7 ", s) are updated periodically to follow the emergence of network traffic. In the wrong view, an alarm is sound indicating the arrival of a network service anomaly if (I) the approximate size (in real time) of traffic is ,,,,,,, r, ~ T ,,,) while T,, s deviates from the threshold more than from on the first predicted basis, and (2) the previous situation persists and in addition to the Sparsest, e.g.

$$\left[\tilde{I}_s(T_{n,s}) - 2\tilde{\sigma}_s(T_{n,s})\right] - a\tilde{I}_s(T_{n,s}) \geq I_{s,measured}(T_{n,s}) \text{ or}$$
$$I_{s,measured}(T_{n,s}) \geq \left[\tilde{I}_s(T_{n,s}) + 2\tilde{\sigma}_s(T_{n,s})\right] + a\tilde{I}_s(T_{n,s}).$$

The choice of parameters in the above determination mode (a and TPurTlrr) is determined by testing. At this launch an alarm goes off signaling the arrival of unequal network service if the estimated size (in real time) of traffic I ,,,,,,,, ~ LT,) during T, exceeds the limits of more than 50% of the predicted base and more than 15 minutes, ie,

$$\left[\tilde{I}_s(T_{n,s}) - 2\tilde{\sigma}_s(T_{n,s})\right] - 0.5\tilde{I}_s(T_{n,s}) \leq I_{s,measured}(T_{n,s}) \text{ or}$$
$$I_{s,measured}(T_{n,s}) \geq \left[\tilde{I}_s(T_{n,s}) + 2\tilde{\sigma}_s(T_{n,s})\right] + 0.5\tilde{I}_s(T_{n,s})$$

The selection of parameters in the above case (2, 15minutes and 50%) is specified for TAS, and for the following reasons. First, the TAS network is set to deliver 15-minute discovery performance data. Therefore, events that persist in less than 15 minutes are impossible to detect in real time. Second, 2 and 50% parameters were selected in the test. It has also been proven to work well in the TAS area. The user graphic interface (CUI) consists of (1) a control panel, (2) an alarm log, and (3) a traffic indicator. The control panel displays information regarding the performance of service categories and the values of their dynamic parameters, in addition to providing a database-SQL system debugging window. The alarm log summarizes and separates the negative findings and their magnitude. The traffic indicator provides a clear picture of the strength of the road based on the level of service in real time. An example of a service phase view is shown in Figure 8.

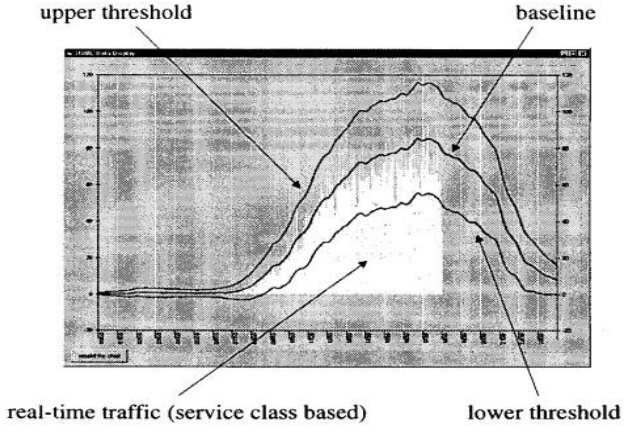

Fig 8- Graphical Representation

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V-ANOMALY DETECTION DEMONSTRATION

In this section we demonstrate the power of the network anomaly detection system by which we have improved detection and network errors. Directly in Figure 9a we look at a PDF of the service category during an unusual operation (an unusually large number of long-term transactions), while the unpleasant case of the same service category is shown in Figure 9b. During the normal operation of another service category (single credit card) failed resulting in excessive accumulation of circuit within the network.

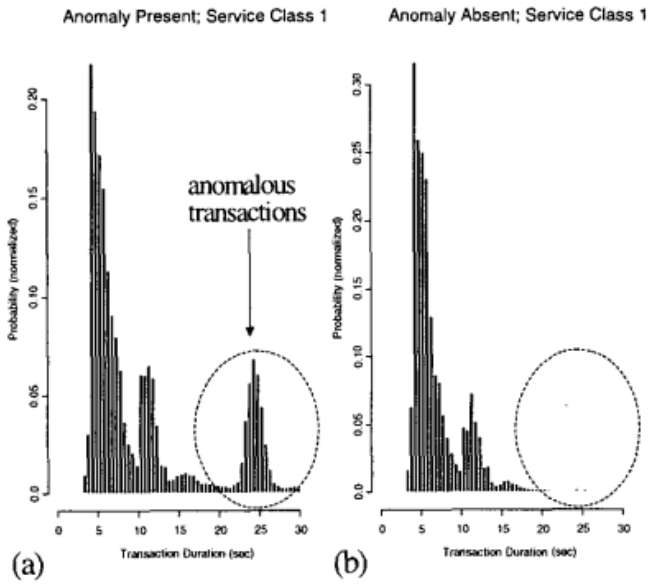

Fig 9-(a) PDF of anomalous service class (b)PDF of same service class with anomalous transactions

In figure 10 we present an example of the detection of a criminal service (a case related to Figure 9a). Performance ratings used at this time by traffic power. A set of strong limits (upper and lower limit) is a dynamic function of predictable core performance and tolerance.

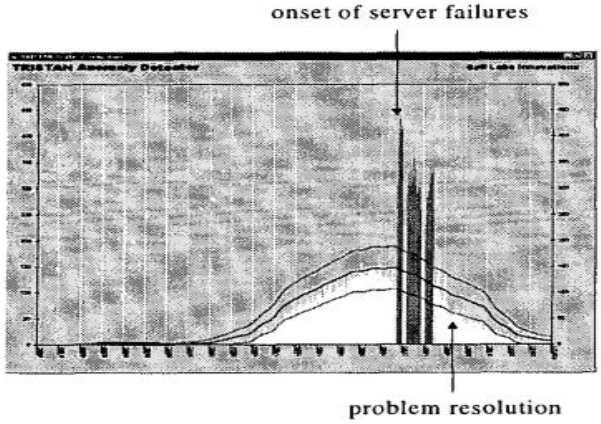

Fig 10- Traffic Intensity of faculty service class detected by anomaly detector system

VI- CONCLUSION

In this paper we present the methods and algorithms we have developed with the aim of improving the effective and flexible removal of network service malfunctions (failures and operational corruption) in sales based on Electronic Commerce Wide Area Networks. The proposed method and algorithms are able to detect Il On-irivial network malformations from within and outside the network. These are called io: (1) a performance-enhancing sample that emphasizes potentially unstructured transactions, (2) a threshold generator that limits the robust performance of various service classes, and (3) a detector that makes offline discovery. We are currently working on expanding and exploring the field with error detection strategies across a wide range of communication sites, such as IP and wireless local networks, where reduced service performance and errors can significantly affect qtlality-of-service (QoS) and network availability.

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