First Fault Performance Problem Resolution

Fix Mainframe Performance Problems Right the First Time

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in collaboration with

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Introduction

For large enterprises the data center is a critical part of their business infrastructure. New market requirements – such as web based customer self service, globalization, and increased business agility are leading businesses to create new applications that are heavily reliant on existing legacy transaction computing infrastructure and applications. These new applications place heavy performance requirements on existing infrastructure and applications. This has made system performance even more business critical today than a decade ago. Since almost all of an enterprise's transactions interact with mainframes (which contain 70% of the world's business critical data) during processing, any slowdown has an immediate effect on the business, and a severe, long duration problem can be catastrophic. Over the years, excellent system monitoring tools have evolved but they aren't enough to provide the level of support needed by these new usage paradigms. These new applications and usage paradigms are straining mission critical mainframe applications and IT staff to the limit.

As a result, existing IT staff is being called upon to provide flawless service response and immediate problem resolution for application issues. Most production service degradation issues are related to unexpected and unplanned interferences between applications and transactions on the production system, making it impossible to provide flawless, 100% problem free operation - no matter how good your staff or monitoring solution. This leaves IT staff scrambling after the fact to discover and analyze the complex interactions that cause performance degradation – in most cases waiting for the problem to surface again before it can be fixed. Instead of after the fact detective work to solve performance problems, IT management and operations should focus on **first fault problem resolution**. That means both alerting IT staff and capturing all the relevant system data during a performance problem so that the IT staff will have a post-mortem detailed view of the system status right before, and during the problem's occurrence. Making this data available to the staff allows them to solve a problem the first time it occurs – providing a dramatic reduction in mean time to repair for transaction slowdowns and performance degradation.

Background

ConicIT was founded based on the observation of a fundamental weakness of commonly used performance monitoring systems, namely the time lag between problem occurrence (when meaningful analyzable factors are available) and problem detection, when the data is only symptomatic. It became clear that if it was possible to predict problem occurrence before the data becomes dominated by symptoms, it will greatly facilitate and enhance the process of root cause analysis.

There are several factors make that task extremely challenging:

- The problems are rare by definition, which poses a known difficulty to existing statistical prediction algorithms
- The number of potentially relevant features is very high, hence increasing the complexity and the data requirements for obtaining reliable predictions
- The data is non-stationary, hence ruling out most of the existing statistical methodologies
- Extremely noisy data, where the measurement noise often obscures the underlying phenomena of interest.
- The limitations of commonly used threshold-based methods, which disregard important interrelations between critical performance variables.

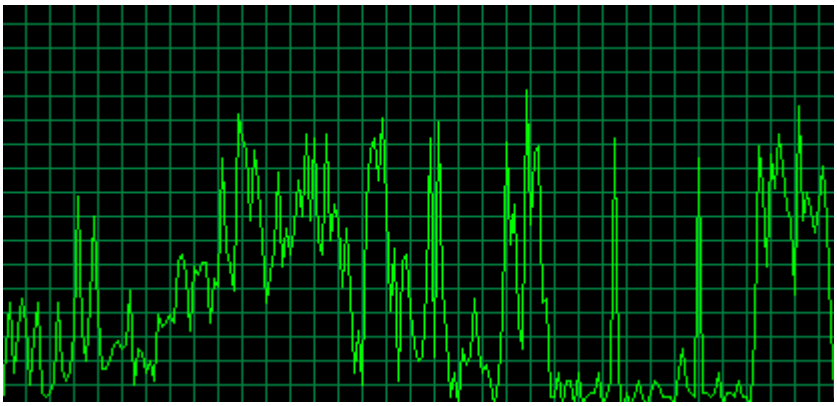
To address those issues we developed ConicIT for Mainframes, a unique product that uses sophisticated mathematics and algorithms to solve the problem of alerts and root cause analysis for mainframe systems:

- State-of-the art data cleansing algorithms, based on jump-diffusion models, non-linear Monte-Carlo filtering, and dynamic modeling, to address the non-stationary and non-linearity of the monitored signals, among other issues.
- A methodology for generation of composite problem detection criteria, taking into account the inter-correlation between the variables of interest.
- Advanced multi-expert prediction algorithms for look-ahead detection of emerging problems, that greatly facilitate the problem cause analysis.

ConicIT System Overview

ConicIT runs on a separate Linux system external to the system being monitored. ConicIT is a completely agentless architecture which doesn't require installation on the system being monitored. It receives data from existing monitors (e.g. Omegamon, TMon, Sysview, Mainview) through their standard interfaces. For mainframes, 3270 emulation enables ConicIT to appear as just another operator to the existing monitor and adds no more load to the monitored system than would adding an additional human operator. Until a problem is predicted ConicIT requests basic monitor information at a very low frequency (about once per minute), but if the ConicIT analysis senses a performance problem brewing, its requests for information increase, but never so much as to effect the monitored system. The maximum load generated by ConicIT is configurable and ConicIT supports all the major mainframe monitors.

The monitor data stream is retrieved by parsing the data from the various data sources. This raw data is first sent to ConicIT's data cleansing component. Data from existing monitors is very "noisy", since various system parameters values can fluctuate widely even when the system is running perfectly. **Graph 1** shows sample CPU utilization measurements over time from a perfectly normal system. Even though the CPU utilization is deviating greatly from the mean – it is not necessarily indicative of a system problem. The job of the data cleansing algorithm is to find meaningful features from the fluctuating data. Without an appropriate data cleansing algorithm it is very difficult or impossible for any useful analysis to take place. Such cleansing is a simple visual task for a trained operator, but is very tricky for an automated algorithm.



Graph 1: Normal CPU Fluctuations

The relevant features found by the data cleansing algorithm are then processed to create appropriate variables. These variables are created by a set of rules that can process the data and apply transformations to the data (e.g. combine single data points into a new synthesized variable, aggregate data points) to better describe the relevant state of the system.

These processed variables are analyzed by models that are used to discover anomalies that could be indicative of a brewing performance problem. Each model looks for a specific type of statistical anomalies that could predict a performance problem. No single model is appropriate for a system as complex as a large computing system, especially since the workload profile changes over time. So rather than a single model, ConicIT generates models appropriate to the historical data from a large, predefined set of prediction algorithms. This set of active models is used to analyze the data, detect anomalies and predict performance degradation. The active models vote on the possibility of an upcoming problem in order to make sure that as wide a set of anomalies as possible are covered, while lowering the number of false alerts. The set of active models change over time based on the results of an offline learning algorithm which can either generate new models based on the data, or change the weighting of existing models. The learning algorithm is run in the background on a periodic basis.

When a possible performance problem is predicted by the active models, the system takes two actions. It sends an alert to the appropriate consoles and systems, and also instructs the monitor to collect information from the effected systems more frequently. The result is that when IT personnel analyze the problem they have the information describing the state of the system and the effected system components as if they were watching the problem while it was happening. The system also uses the information from the analysis to point out the anomalies that led the system to predict a problem, thereby aiding in root cause analysis of the problem.

System Components

As shown in **Figure 1**, ConicIT's system architecture consists of 3 major components:

1. A data cleansing component
2. A rule analysis component
3. An expert system and learning component

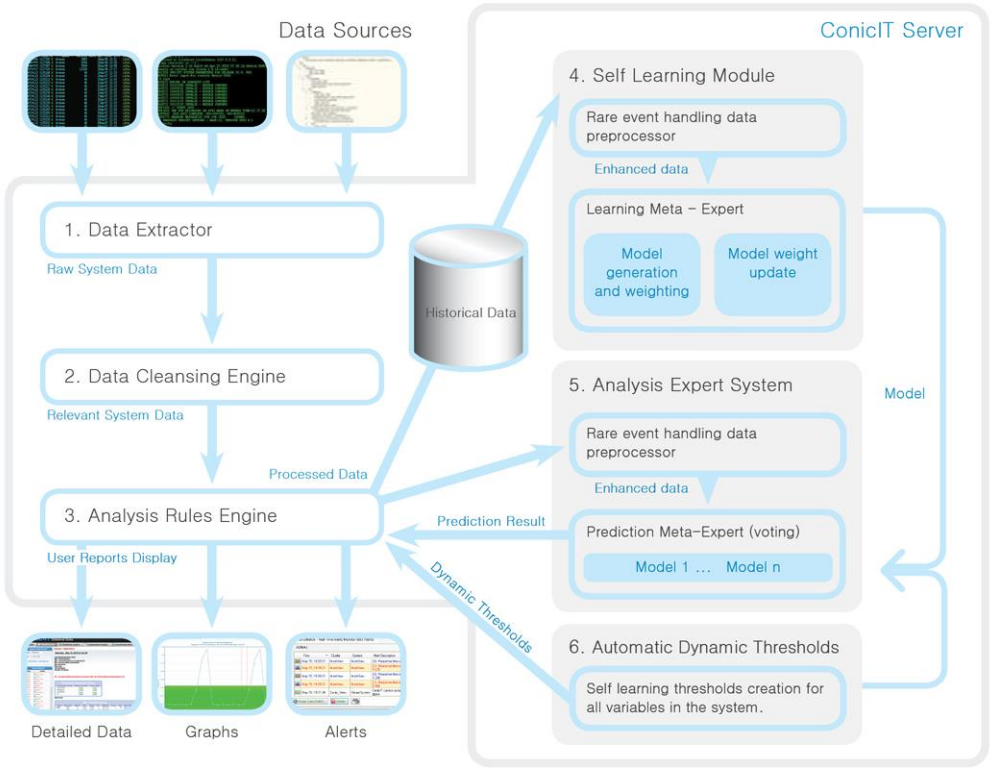


Figure 1: ConicIT Major Component Overview

Data Extraction and Cleansing (1,2)

The system interfaces with the system monitors and other data sources through standard (3270) emulation. The systems appears as just another user to the monitors, and requests data from monitors on a regular basis. This data is then parsed into a form usable by the data cleansing component.

This raw stream of data enters the data cleansing component as a set of simple and complex variables obtained by simple preprocessing of the 3270 data stream. The data cleansing algorithm then uses various sophisticated mathematical models to decide what data should be passed the next stage for analysis. The enormous fluctuations in systems data make standard filters and statistical analysis irrelevant. For example, looking at the data in **Graph 1** it is clear that thresholding won't work – it will cause either too few or too many alerts, depending on how the threshold is set. Using the mean is equally uninformative.

ConicIT uses a proprietary data cleansing algorithm that is fast enough to analyze the real time data stream while ensuring that the analysis engine is not swamped with irrelevant data.

Analysis Rule Engine (3)

This component takes relevant data provided by the data cleansing component and uses it to create specific variables appropriate for performance analysis. This allows the system to easily support new monitors, since when adding a new monitor only the preprocessing needs to be changed, not the data cleansing component. ConicIT configuration set up also allows for easy mapping between the 3270 data stream and variables needed by expert system, and it also enables the use of multivariate data (creating a synthetic variable that represents the merged behavior of more than just a single measured variable) which enables the models to use correlated variables to find anomalies.

The analysis rule engine is also responsible for data manipulation related to end user needs (e.g. data aggregation for user display) and for creating all of the user notifications and reports. This engine uses the relevant data it obtains from the data cleansing component and results from the expert system to create end user screens, reports and alerts.

The analysis rule engine is implemented as rules in a standard scripting language (PERL) and can be easily extended.

Self Learning Module and Analysis Expert System (4,5,6)

These are the modules that are responsible for the actual prediction of possible performance degradation. They receive as input the processed data (variables) from the analysis rules engine and use it as input for both the prediction and learning algorithms.

The first step for both the expert systems and self-learning module is a rare event preprocessor. Since system anomalies are statistically rare there is a need to process them before they are appropriate for use by the prediction algorithms and models. This component takes the processed data (variables) and transforms it to enhanced data appropriate for the prediction of rare events.

Self Learning Module (4)

The learning mechanism is an offline algorithm that uses historical data to periodically check the prediction algorithms in order to select the most appropriate set of active models for the current state of the monitored system. The self learning module applies the historical data to candidate prediction algorithms to create prediction models and a weight for each model. The set of active models cannot be too large since they need to be calculated in real time against the feature set provided by the data cleansing component.

ConicIT comes out of the box with a large set of prediction algorithms appropriate for most mainframe installations. Achieving optimal performance for a specific installation requires about a week of site specific professional services tailoring and a equivalent automated learning period.

Analysis Expert System (5)

This is the run time component used for predicting possible performance degradation. It uses the current enhanced data, and uses a voting algorithm to generate a score defining the probability of possible service degradation. The voting algorithm examines uses all of the active models and their weights to provide a numerical prediction of performance degradation and it also provide a vector of all the variables that led to the decision (to be used for root cause analysis).

Dynamic Thresholds (6)

Because of the changing production environment in real world installations, static alert thresholds are inappropriate and create more problems than they solve. To take into account this changing environment, the system automatically calculates dynamic thresholds for the parameters of interest. These thresholds are used by the rules engine to decide whether an alert is warranted, what type and of what severity.

ConicIT in Action

Resource Contention

A large organization was experiencing intermittent performance slowdowns that affected various mainframe transactions, and there seemed to be no pattern to the slowdowns. Not surprisingly, by the time a slowdown was noticed, the relevant system information was no longer available via the monitor and not available in any log, making problem determination extremely difficult. This led them to install ConicIT to see if it could assist in diagnosing the problem.

ConicIT was installed to learn the standard behavior of the system. As part of that learning process, ConicIT's prediction models learned the system's standard behavior relating database resource availability and CPU thread activity to CICS transaction response time. As a result of the learning, when ConicIT sensed that DB2 resource wait time was starting to rise above the norm, it understood that this might be a predictor of a brewing transaction response time problem. This caused ConicIT's prediction engine to proactively collect monitor information related to transaction response time, CPU thread information and DB2 resource usage- before the slowdown actually occurred.

The next time the problem occurred; ConicIT had predicted the problem and collected the relevant information before the actual slowdown was noticed. Using this information, the system programmers understood exactly the state of the system during, and immediately before, the slowdown occurred. The results of the analysis showed that there was a specific set of transactions that were heavy users of database resources, and when they occurred together could cause a general response time slowdown for the whole system.

Batch Window Overrun

Another customer problem occurred after ConicIT had been installed for a while. A problem occurred over the weekend in handling transactions coming from Automated Teller Machines (ATM). On the Monday after the event, they were greeted by alerts regarding performance slowdowns over the weekend. None of the problems were severe enough to cause a panic over the weekend, but needed to be resolved to ensure that they weren't indicative of a deeper issue.

The standard logs and monitors showed nothing unusual about the ATM transactions that occurred during the slowdown. However, ConicIT's prediction engine had noticed a database resource contention issue (through anomalies in the DB2 resource usage information) and used

that information to predict possible CICS transaction response time problems. That prediction caused ConicIT to start collecting system information regarding the state of the database involved and the transactions that took place during the slowdown. From that information, it was immediately clear to the system programmers that there was a standard overnight batch process that had overrun its batch window during which it had locked the database. This occurred since the batch program had needed to process an unusual amount of information received on the Friday before the weekend.

Generalized Example

As ConicIT learns the system over time, it creates models of how system parameters should behave and how they may affect each other. In this example, ConicIT used its model of past CPU behavior to discover a non-standard behavior pattern of CPU unrest. Since the prediction model understood that such behavior may be indicative of future performance problems, it used that anomaly as the basis to request additional monitoring information (e.g. MVS) to analyze external resources (e.g. TSO) that could have also been accessing the CPU and causing the anomalous behavior, especially any dispatching waits. ConicIT also started requesting additional monitoring information from CICS, to analyze whether the anomaly could be explained as a temporal phenomenon (e.g day of the week) or as a result of CICS transaction dispatching waits or an internal CICS QRTCB.

As a result of its analysis of all of this data the ConicIT analysis rules engine would decide whether to issue an alert. The collected data and the reasoning that triggered the data collection are stored by ConicIT for later analysis. The goal is that once an alert was issued, system programmers will have all the relevant information at their fingertips along with a basic causal analysis – all without putting noticeable load on the system being monitored. It will be up to system programmers to solve the problem, but the diagnosis becomes an order of magnitude easier.

Summary

As opposed to the assumptions of the 1990's - mainframes are here to stay and mainframe usage continues to grow and evolve. Performance issues continue to plague even the most efficient mainframe installations, and the costs associated with mainframe performance issues are of great concern to CIOs. There are more than 200 billion lines of mainframe code running today's businesses worldwide. Fortune 500 companies maintain 35 million lines of COBOL code and add 10 percent more new lines of mainframe code annually just to keep up with business needs, changing conditions, and regulations. These applications still manage and process most customer, product, supply-chain, and critical business data and most are a mix of screen processing, data I/O, and the core of the application—the enterprise's business rules.

The performance and reliability requirements from these mainframe applications are growing while the number of developers who truly know the applications and systems is decreasing. Even though mainframe systems have robust monitoring and management capabilities, mainframe IT personnel are buckling under the strain of supporting all the business IT requirements, and there is a growing gap between the number of mainframe personnel needed and those available. The existing IT personnel need tools that augment existing management and monitoring tools to support them in the analysis and repair of system performance issues in less time and the first time they happen.

ConicIT's technology is uniquely positioned to solve these problems.