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МЕТОД БАЛАНСИРОВКИ НАГРУЗКИ ВЫЧИСЛИТЕЛЬНОГО КЛАСТЕРА ЦЕНТРА ОБРАБОТКИ ДАННЫХ

METHOD OF LOAD BALANCING FOR COMPUTER CLUSTER OF DATA PROCESSING CENTER

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Аннотация

В статье представлено описание метода балансировки нагрузки вычислительного кластера центра обработки данных (ЦОД) в основу которого положен вероятностный подход упреждающего прогнозирования состояний пакетного трафика, сформированный на основе результатов его статистического, нелинейного и спектрального анализа. Фрактальные свойства сетевого трафика являются обоснованием возможности предсказания, позволяют с достаточно большой вероятностью прогнозировать появление на отдельных временных интервалах всплесков и спадов его активности, выявление периодов возможной перегрузки серверов и сетевого оборудования и делают возможным разработку методов эффективного планирования и распределения задач внутри ЦОД, обеспечение статистически равномерной загрузки его функциональных элементов. Спектральный анализ временного ряда проводится по нормированным отклонениям фактических уровней от сглаженных. Отсутствие существенных пиков спектральных оценок говорит об отсутствии периодических колебаний. Показано, что суммирование циклов разного периода динамики временного ряда, основанное на использовании наиболее значимых гармониках спектра, определяет моменты возникновения последующих аномалий его развития. В основу процесса выявления существенных гармоник спектра положено исследование его спектральной плотности мощности с помощью преобразования Фурье. Разработанный метод способен обеспечить решение задачи эффективного планирования и распределения задач вычислительного кластера ЦОД с целью оптимизации использования ресурсов, ускорения времени выполнения задач и сокращения расходов на обработку приложений.

Ключевые слова: пакетный трафик, временные ряды, фракталы, балансировка нагрузки, функция автокорреляции, гармонический анализ, нелинейная динамика.

Abstract

The article presents a description of the load balancing method for a computing cluster of a data processing center (DPC), which is based on a probabilistic approach to proactive forecasting of packet traffic states, formed on the basis of the results of its statistical, nonlinear and spectral analysis. The fractal properties of network traffic are the rationale for the possibility of prediction, allow with a fairly high probability to predict the appearance of bursts and drops in its activity at certain time intervals, identify periods of possible overload of servers and network equipment, and make it possible to develop methods for effective planning and distribution of tasks within the data center, ensuring a statistically uniform loading its functional elements. The spectral analysis of the time series is carried out according to the normalized deviations of the actual levels from the smoothed ones. The absence of significant peaks in the spectral estimates indicates the absence of periodic fluctuations. It is shown that the summation of cycles of different periods of the dynamics of the time series, based on the use of the most significant harmonics of the spectrum, determines the moments of occurrence of subsequent anomalies in its development. The process of identifying significant harmonics of the spectrum is based on the study of its spectral power density using the Fourier transform. The developed method is able to provide a solution to the problem of efficient planning and distribution of tasks in a data center computing cluster in order to optimize the use of resources, speed up task execution time and reduce application processing costs.

Keywords: packet traffic, time series, fractals, load balancing, autocorrelation function, harmonic analysis, non-linear dynamics.

Introduction

The computing resources of the data center of cloud systems are implemented in the form of server clusters and a system for distributing and balancing the load. The task of the load distribution and balancing system is to implement a method that provides an approximately equal computational load on the elements of the data center information system, as well as minimal data transfer costs. The purpose of this study is to improve the efficiency of the functioning of data centers that provide information services through the use of a packet traffic management method based on its fractal and harmonic analysis. The block diagram of the data center information cluster, shown in Figure 1, contains many servers and a load balancing system that distributes requests based on server status monitoring information.

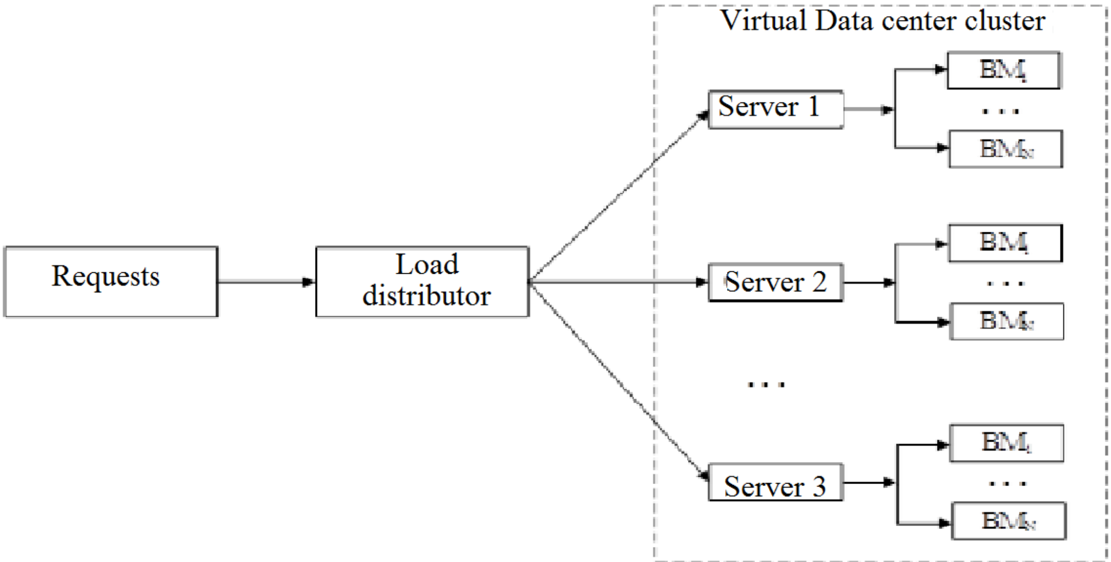

Figure 1. Structural diagram of the data center information cluster

One of the most important factors affecting the efficiency of data centers is network traffic anomalies, which consist in its fractality (self-similarity), frequent bursts and drops in activity, a cyclic component, powerful peak emissions and, as a result, system overload. Detection of such anomalies, timely prediction of the time of their occurrence in the future, in order to take measures to ensure the quality of service, necessitates the creation of more efficient methods for managing a distributed system of data center clusters. It is known [1,3,5] that the properties of the scale invariance of network traffic can provide, by analyzing over a short period of time, a prediction of its behavior over longer intervals, thus ensuring the implementation of effective planning and distribution of tasks within the data center, statistically uniform loading of its functional elements . A measure of the duration of the long-term dependence of a random process, which provides the definition of its fractality (self-similarity), the presence of cycles, long-term memory, and stability, is the Hurst self-similarity parameter N. A short-term forecast of network traffic states is also provided by the Fourier transform and spectral analysis [2,4]. The main advantage of spectral analysis lies in its ability to identify the most significant harmonics of the spectrum of the process under study. Identification of the most significant harmonics of the time series characterizing the dynamics of network traffic is based on estimating the spectral power density of the process using the discrete Fourier transform, obtaining the complex amplitudes of the data series, and then calculating its power spectrum. This decomposition is a spectrum of network traffic dynamics. The points of maximum values of the amplitudes of the spectrum indicate cycles of periodic oscillations of various lengths. If we select these cycles from the general spectrum of network traffic, and then sum them up, then we can determine the further dynamics of the development of traffic anomalies, the time of occurrence of subsequent powerful bursts of its activity, predict the parameters of the most probable peak load and the moments of its occurrence. This study proposes a method for distributing and balancing the load, which improves the efficiency of the data center by solving the problem of short-term forecasting of network traffic states in time and forming on this basis control decisions aimed at maintaining a uniform load on the data center equipment.

1. Research methodology

Experimental studies [6,9,12] confirm the fractal (self-similar) structure of network traffic. It is known that fractal network processes have a long-term dependence, which is expressed in an almost infinite correlation interval and makes it possible to predict its state in subsequent time intervals [14]. To implement an effective load balancing system, to ensure statistically uniform loading of many servers in data center clusters, it is necessary to take into account the structure and properties of network traffic, and to predict the magnitude of possible load intensity jumps. The solution to this problem is possible by applying a dynamically changing algorithm for distributing and balancing the load, built on the basis of a statistical analysis of the network traffic entering the system, assessing the degree of its fractality, Fourier series and harmonic analysis. The monitoring data of the data center input load used to implement the control action on the load balancing system can be represented as numerical series characterizing changes in its parameters over time. Spectral analysis makes it possible to determine the most significant harmonics of the spectrum of the obtained time series from all M harmonics, which are in its various samples and have the largest amplitude. The periods of the most significant harmonics of the spectrum determine the periodicity of the cycle. If we separate these harmonic components of the spectrum from its general dynamics, and then present them as a sum of cycles of different periods, then we can determine the further dynamics of the development of the process, as well as provide the possibility of predicting its further development. The algorithm for solving this problem includes the following steps:

1. Monitoring the input load of the data center, presenting it as a time series, determining the degree of fractality of packet traffic using the Hurst exponent.
2. Determination using the method of least squares of the linear trend of the time series.
3. Removing a trend from the original time series.
4. From the newly formed time series, the selection of harmonics corresponding to the highest coefficient of determination and adding them to the model of the dynamics of the time series.
5. Calculation of Durbin-Watson statistics for the presence and level of autocorrelation. Confirmation of the acceptable quality of the regression model.
6. Definition of cycles, forecast of their development.
7. Based on the analysis of the fractal properties of network traffic, as well as data on server load, the implementation of a new load distribution.

2. Study of the Hurst exponent.

The process of network traffic entering the distribution and load balancing system of the data center is described by the model [7,8,10]

$$Y_t = F_{TP}(t) + \sum_{k=1}^{M} Y_k + \varepsilon_t \tag{1}$$

where $F_{TP}(t)$ is a long-term trend, trend;

Y_k are the harmonics of the Fourier series;

ε_t is a random variable .

The presence of a trend in the aggregation interval of packet traffic, presented as a time series, determines the H -Hurst index, which is a characteristic of the stability of the statistical process, an assessment of the correlation between its elements and is determined by R / S analysis. The proximity of the parameter H to 1 determines the sufficient trend stability of the process and the possibility of predicting the degree of its change over time. The basic formula of R / S analysis is the expression [11]

$$R/S = (a \cdot N)^H , \quad (2)$$

where H is the Hurst exponent;

N is a sample of length N;

S is the standard deviation of the obtained measurements;

R is the range of relations $R = \max(Z_u) - \min(Z_u)$;

Z_u is the accumulated deviation of the series from the mean $x_{cp.}$;

a is a constant;

$S = \sqrt{N^{-1}} \cdot \sum_{i=1}^{N} (x_i - x)^2$.

Taking the logarithm of the resulting expression, we obtain

$$H = \log(R/S)/\log(N/2).$$

At $0,5 < H < 1$, we have a persistent or trend-stable series. The influence of the present on the future is described by the measure of correlation [13]

$$C = 2^{2H-1} - 1.$$

The Hurst coefficient H is a measure of the duration of the long-term dependence and describes all other fractal parameters of the process under study [15,17]:

- fractal dimension $D = 2 - H$;
- correlation parameter $\beta = 2(1 - H)$;
- spectral index $b = 2H + 1$;
- fractal index $a = 3 - 2H$.

For a self-similar process $x(t)$ with the $0,5 < H < 1$ correlation function decays hyperbolically [12]

$$R(K) = \frac{\sigma^2}{2}\left[(K+1)^{2H} - 2K^{2H} + (K-1)^{2H}\right].$$

By definition, the correlation coefficient

$$\tau(K) = R(K)/R(\sigma) = R(K)/\sigma^2 ,$$

hence the autocorrelation function (ACF) will have the form

$$\tau(K) = \frac{1}{2}\left[(K+1)^{2H} - 2K^{2H} + (K-1)^{2H}\right]. \quad (3)$$

The calculation of the ACF must be carried out in order to assess the nature of the decrease in the dependence of the elements of the time series.

The numerical values of the ACF can be obtained from the formula [14]

$$\tau(K) = \frac{\sum_{i=1}^{N-K} (x_i - \overline{x})(x_{i+k} - \overline{x})}{(N-K)\sigma^2(x)} , \quad (4)$$

where $\overline{x}$ is the average value of the *x series*;

$\sigma^2(x)$ is the variance of the x *series* ;

K - time lag.

A slow decrease in ACF values characterizes a slowly decreasing dependence between traffic elements. A rapid decrease in the ACF values is a sign of the stationarity of the process under study. For fractal processes characterized by the properties of self-similarity and slowly decreasing dependence, the autocorrelation function does not vanish when $t \to \infty$.

For a more accurate description of the measure of the long-term dependence of a self-similar process, inhomogeneous fractal objects, or multifractals, are used [15]. In this case, the original time series $x(t)$ is divided into N segments of length S and for each segment

$$y(t) = \sum_{i=1}^{n} x(t),$$

Function is defined

$$F(s) = \sqrt{\frac{1}{S}\sum_{t=1}^{T}\left(y(t) - y_m(t)\right)^2}.$$

Next, find the dependence $F_q(S)$ on a fixed value q

$$F_q(S) = \left\{\frac{1}{N}\sum_{i=1}^{N}\left[F^2(S)\right]^{\frac{q}{2}}\right\}^{\frac{1}{q}}$$

By changing the length S of the time series, for arbitrary values of q , we find the sequence of values $F_q(S)$. If a $F_q(S)$ seems to depend [16]

$$F_q(S) \sim S^{h(q)},$$

then the time series corresponds to the multifractal set and has a long-term dependence on the Hurst exponents $h(q) = H$.

3. Harmonic analysis.

It is known that R / S -analysis does not always give correct estimates of the Hurst exponents. A method based on correlation analysis gives greater statistical accuracy. If the expression is true

$$\tau_k = k^{-\beta} L(k) + C,$$

where C – const , $0 < \beta < 1$;

$L(k)$ is a slowly changing function $\lim\limits_{t\to\infty}\frac{L(tx)}{L(t)} = 1$, .

then such a process is described by an ACF decreasing according to a power law [12].

When describing a network process, it is preferable to use a harmonic function of the form

$$Y_t = \bar{Y}_t + \sum_{k=1}^{M} a_k \cdot \cos\frac{2\pi kt}{N} + \sum_{k=1}^{M} b_k \cdot \sin\frac{2\pi kt}{N} \qquad (5)$$

where $a_k = \frac{2}{N}\sum_{k=1}^{M} Y_t \cdot \cos\frac{2\pi kt}{N}$,

$b_k = \frac{2}{N}\sum_{k=1}^{M} Y_t \cdot \sin\frac{2\pi kt}{N}$, are the harmonics of the Fourier series ;

M is the number of harmonics in the series;

N - row length.

To describe the long-term trend of the time series, we use the function [12]

$$\bar{Y}_T = A_1 \sin\left(\frac{2\pi t}{P}\right) + A_2 \cos\left(\frac{2\pi t}{P}\right) + A_3. \quad (6)$$

The period P of the trend cycle is obtained by sequentially dividing its most probable value into equal time intervals P_i and, using regression methods, we determine the coefficients A_1, A_2, A_3. Next, we select the sequence of time intervals in which

$$\frac{1}{T}\sum_{t=1}^{T}\left(Y_T - F_{TP}\left(t, P_i\right)\right)^2 \to \min .$$

The choice of a model that describes the long-term trend of the network process is based on an assessment of its accuracy. Obviously, models that provide a smaller discrepancy between real and calculated values provide greater accuracy. It is most expedient to use the following expressions as indicators of accuracy [17]

a) difference of variances $V_{ar} = \frac{1}{T}\sum_{t=1}^{T}\left(Y_t - F_{TP}\left(t\right)\right)^2$;

b) approximation error $A = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{Y_t - F_{TP}}{Y_t}\right|$;

c) indicator of process determination

$$R^2 = \frac{\sum_{t=1}^{T}\left(F_{TP}\left(t\right) - \bar{Y}\right)^2}{\sum_{t=1}^{T}\left(Y_T - \bar{Y}\right)^2},$$

where $\bar{Y} = \frac{1}{T}\sum_{t=1}^{T} Y_t$ is the average value of the elements of the time series.

The theoretical number of frequencies is chosen equal to N/2 with the length of the series equal to N. In practice, not all N/2 are required, but only some harmonic components that express the main part of the variation of the series. To eliminate random fluctuations and possible errors in the estimated traffic values, the resulting non-stationary time series must be additionally processed. A possible solution in this case is to exclude its trend by smoothing the dynamics, for example, using the centered moving average method, or second-order moving parabolas, i.e. use absolute or normalized deviations of the time series from its long-term trend.

To identify regular periodic cycles that make the greatest contribution to the overall dynamics of the network process, we remove the trend from the time series structure. The forecast of the periods of cycles is built by highlighting the harmonics of the spectrum of the time series with the largest amplitudes, the formation of the corresponding model and its extrapolation. The function by which the Fourier transform of the studied time series is calculated has the form [18]

$$f\left(x\right) = \frac{a_0}{2} + \sum_{m=1}^{M}\left[a_m \cos\left(m\frac{2\pi}{X_{\max}}\right) + b_m \sin\left(m\frac{2\pi}{X_{\max}}\right)\right],$$

where $a_m = \frac{2}{N} + \sum_{n=0}^{N-1} y_n \cos\left(m\frac{2\pi n}{N}\right), 0 \le m \le M;$

$$b_m = \frac{2}{N} + \sum_{n=0}^{N-1} y_n \sin\left(m\frac{2\pi n}{N}\right), 0 \le m \le M;$$

M is the number of harmonics of the studied series;

(x_n, y_n) – array of sample and values of the time series;

$n = 0,..., N$.

It is known [14] that in order to select from all M most significant time series harmonics, Fourier series expansion is used

$$f(x) = \frac{a_0}{2} + \sum_{m=1}^{M} \left[R_m \cos\theta_m \cos\left(m\frac{2\pi}{N} \right) + R_m \sin\theta_m \sin\left(m\frac{2\pi}{N} \right) \right],$$

where $R_m = \sqrt{a_m^2 + b_m^2}$,

$\theta = -arctg\,\frac{b_m}{a_m}, \ -\pi \le \theta_m \le \pi;$

$a_m = R_m \cos\theta_m,$

$b_m = -R_m \sin\theta_m.$

Denoting the oscillation frequency as $\omega_m = m/N$, we write the Fourier distribution in the form

$$f(x) = \frac{a_0}{2} + \sum_{m=1}^{M} R_m \cos(2\pi\omega_m n + \theta_m),$$

where $T_m = \frac{1}{\omega_m}$ is the cycle period of the time series.

To obtain numerical values of the amplitude and phase of the most probable cycles of the time series, we use the expressions [13]

$$A_n = \frac{1}{n}\sqrt{R_e^{\,2}(S_n) + I_m^{\,2}(S_n)}$$

$$\varphi_n = arctg\,\frac{I_m(S_n)}{R_e(S_n)},$$

where S_n is the set of frequencies of possible cycles.

Then, the cycle can be described by the expression

$$f_n(t) = A_n \cos(S_n t + \varphi_n).$$

If we represent the dynamics of bursts of network traffic as the sum of a set of cyclic components, then the periodicity of the time series will be equal to

$$V(t) = \sum_{D} f_n(t),$$

where D is the set of possible cycles of the series.

The sequence of stages for selecting cycles of a time series of data:

a) the choice of the initial time series and the determination of its trend using the method of least squares;

b) subtraction of the resulting linear trend from the original time series;

c) from the resulting series, the selection of harmonics that provide the highest coefficient of determination

$$R^2 = 1 - \frac{\sum_{t=0}^{N-1}\left(y_t - Y_t^{garm}\right)^2}{\sum_{t=0}^{N-1}\left(y_t - \bar{Y}\right)}.$$

It is known [17] that for the most accurate models, the coefficient of determination should not be less than 0.8. In this case, the correlation coefficient is close to 1;

d) adding selected harmonics to the time series model;

e) checking for autocorrelation using Durbin-Watson statistics

$$d = \sum_{t=2}^{n}\left(y_t - y_{t-1}\right)^2 \Big/ \sum_{t=1}^{n} y_t^2.$$

The value $1,5 < d < 2,5$ is a confirmation of the acceptable quality of the regression model;

f) definition of short-term cycles.

The obtained dependence Y on the interval $t \in [0,\, N-1]$ makes it possible to determine the values Y on the interval $t \in [N,\, N+m]$.

Using this approach allows you to make a reliable short-term forecast and timely inform the data center balancing system about subsequent significant bursts of network traffic.

4. Nonlinear forecasting.

TCP packet traffic can be described not only as a simple periodic process, but also as a process with more complex behavior and described by methods and models of deterministic chaos. [19]. At the same time, the main method for determining the chaotic nature of this nonlinear process is the spectrum of characteristics, consisting of *n* Lyapunov exponents. The signs of the Lyapunov exponents quite reliably characterize the type of fluctuations in the studied time series. A deterministic chaotic process is determined by positive exponents, a zero exponent determines a quasi-periodic process, a negative exponent is a fixed point of the phase trajectory, called the attractor of the system. Otherwise, all Lyapunov exponents of a deterministic process are negative or equal to zero, while a chaotic process has at least one positive exponent. Using the chaotic properties of the studied fractal process, it is possible to construct a predictive model of its development. The predictive models can be based on the methods of linear, non-linear forecasting, as well as global polynomial approximation [20]. To determine the spectrum of nonlinear parameters of the time series, there is a fairly large set of special software. For example, software packages CDA , Dataplore , RQA , TISEAN . The set of analysis tools implemented on the TISEAN platform provides the determination of a fairly complete range of nonlinear characteristics of a deterministic chaotic process. In this case, the chaotic nature of the process dynamics is determined by the value of the maximum Lyapunov exponent, which characterizes the rate of divergence of its phase trajectories. To determine the Lyapunov exponent, we use the lyap program of the TISEAN package . As a result, we obtain the dependence of the coefficient of $S(\varepsilon, m, \Delta n)$ divergence of trajectories on time [17]

$$S(\varepsilon, m, \Delta n) = \frac{1}{N}\sum_{n_0}^{N} \ln\left(\frac{1}{\left|U\left(S_{n_0}\right)\right|} \times \sum_{S_n \subset U\left(S_{n_0}\right)} \left|S_{n_0+\Delta n} - S_{n+\Delta n}\right|\right),$$

where ε is the neighborhood of the point S_{n_0};

m is the fractal dimension of the phase space;

Δn – time interval;

$U\left(S_{n_0}\right)$ is the neighborhood of the point S_{n_0} with radius ε.

The obtained values $S\left(\varepsilon, m, \Delta n\right)$, for various Δn, characterize the required values of the Lyapunov exponents.

The general model of nonlinear prediction has the form [19]

$$x\left(t+T\right)=\frac{1}{\left|U_m\right|}\sum_{x(t')\in U_m}x\left(t'+T\right),$$

where U_m is the neighborhood of the point $x\left(t\right)$.

This algorithm is implemented by the programs lzo-run, lzo-test, false-nearest of the TISEAN platform.

When using linear prediction, the algorithm [20] is used

$$x\left(t+T\right)=a_n x\left(t\right)+b_n,$$

$$\sum_{x(t')\in U_m}\left(x\left(t'+T\right)-a_n x\left(t'\right)-b_n\right)^2\to\min.$$

The predictive method of global approximation is implemented by the expression [20]

$$\sum_t\left(x\left(t'+T\right)-f_T\left(x\left(t'\right)\right)\right)^2\to\min$$

using the FNN program of the TISEAN platform .

Automation of the process of implementing the predictive model can be carried out using the methodology described in [19], using programs for determining the value of the autocor lag . exe , Tayler's window size selection mutual . exe , calculation of correlation dimension d 2. exe .

5. The structure of the load balancing system.

The computing resources of the data center are represented by a set of server clusters and load balancing tools. The structure of the data center load balancing system is shown in Figure 2. At the request of users, the balancing system generates virtual machines (VMs) with certain system indicators. The local manager analyzes the load of the servers and places the incoming requests on them. The data center monitoring system transmits the received information to the global manager, which performs the formation of VMs, manages the load balancing of data center server clusters, and adjusts the system throughput according to the traffic profile. In this case, the following tasks are sequentially implemented:

- receiving requests from subscribers for the implementation of services;
- calculation of network statistics, implementation of the forecasting algorithm;
- distribution of requests across cluster servers;
- selection of a server in the cluster capable of fulfilling user requests;
- sending requests to the selected cluster server;
- distribution of implemented software applications across cluster servers;
- formation of a set of virtual machines that implement applications;
- receiving the results of solving problems.

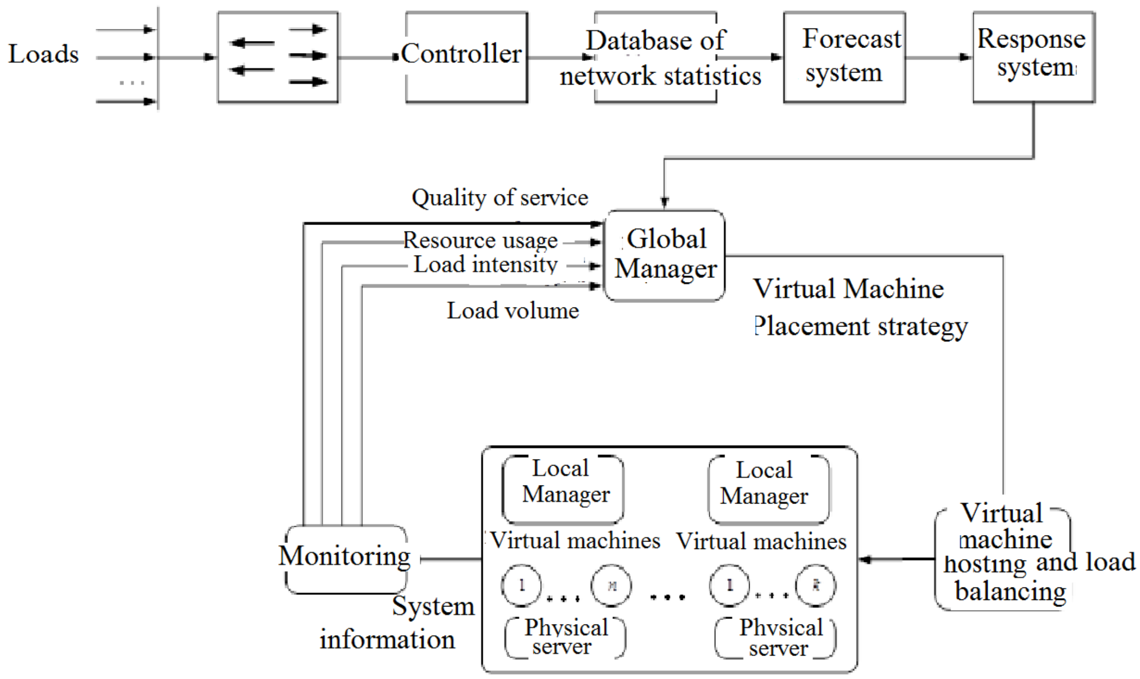

Figure 2. The structure of the load balancing system

To implement the algorithm for predicting anomalies in the network load of the data center, the information structure of the balancing system additionally includes a switch connected via the Gigabit protocol An Ethernet network statistics database with a WireShark sniffer program based on, for example, the WinPcap library , as well as a high-performance controller that implements a prediction algorithm. The sniffer program captures traffic, processes it, aggregates it, forms the required time intervals, and also captures sudden changes in the input load. The resulting level of bursts of traffic intensity, as well as their duration, inform the forecasting system about the need to turn on the aggregation of the response system and redistribute the data center hardware and software at this interval. At the same time, it is obvious that the delay in the control action associated with the process of monitoring network traffic can lead to a decrease in the efficiency of the load distribution and balancing system. Therefore, it is necessary to carry out the formation of a preventive control action, which is directly related to the implementation of the method for predicting the possible peak load and the time of its occurrence.

Conclusion

Experimental studies of the statistical characteristics of packet traffic in modern computer networks indicate its fractal structure, the presence of frequent bursts and drops in activity, powerful peak emissions, and a deterministic component. Such properties of traffic confirm the possibility of using fractal models for predicting bursts of its intensity, determining the volume of incoming traffic with the required accuracy and solving, on this basis, the problems of dynamic control of the distribution system and load balancing of data center cluster servers. The use of classical Markov (without aftereffect) models and Erlang formulas oriented to the simplest flows to calculate the parameters of the load balancing system, as a rule, leads to incorrect results that are inefficient for fractal (self similar) flows. The article presents a description of the load balancing method, which is based on a reliable, probabilistic approach to proactive forecasting of network traffic states, formed on the basis of the results of its statistical and spectral analysis, fractality level, distribution density. The problem of short-term forecasting of packet traffic is reduced to the problem of forecasting a discrete time series. The developed method is able to provide a solution to the problem of efficient planning and distribution of tasks in a data center computing cluster in order to optimize the use of resources, speed up task execution time and reduce application processing costs. The direction of further research related to improving the operation of cloud data centers is to represent them in the form of dynamic systems, the use of nonlinear dynamics methods that allow identifying phase space attractors and providing deeper research on the impact of self-similar traffic on performance.

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