DETECTION AND COMPENSATION FOR DISRUPTIVE NON-LINEAR TRAFFIC-FLOW DYNAMICS IN COMMUNICATION NETWORKS

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ABSTRACT

A method has been developed for the monitoring of traffic flow behavioural dynamics in distributed communication networks and the provision of results from this process to a distributed neural control mechanism which facilitates localised adaptive traffic routing in order to maintain or regain flow stability. It has been shown by simulation how the novel method improves network performance and efficiency beyond that of conventional techniques.

I. INTRODUCTION

IN the current climate of change and growth within the telecommunications industry, the increasing expansion of networks and global communication pathways leads to inevitable loss in performance through the poor capability of some network control systems to balance traffic load effectively and efficiently. Occasions have been noted [1] where entire networks have temporarily failed due to inadequate control mechanisms which find difficulty in dealing with what were once considered as rare events, such as unforecast high volume bursts of traffic arriving onto the communications network.

In the past many networks have been governed by global or domain centralised controllers. These, although providing the ability to plan prospective traffic routes via information tabling, become overloaded when traffic flow intensity increases substantially, beyond expected levels. In order for a interconnected mesh of communicating elements, such as a telecommunications or data network, to interact effectively and efficiently it becomes evident that each element should contain its own control subsystem. The conglomeration of unit element subsystems thereby forms a network-wide distributed mechanism capable of managing traffic flow via localised strategic control. The localised vicinities exchange information through inference; monitoring the activity of neighbouring elements by measuring traffic flow between them and the local controller. In this manner, each element adapts its routing strategies based on a function of its own activity, the activity of its neighbours and forecasts of expected traffic behaviour within its local vicinity.

The research investigates the non-linear behavioural characteristics of traffic within an interconnected mesh of communicating elements, develops mechanisms for monitoring fluctuations within the dynamic behaviour of the traffic and for controlling traffic flow according to tactical decisions based on all available information.

II. TRAFFIC DYNAMICS

The method and results presented within this paper are derived from a model developed for the study of traffic dynamics in communications networks, based on an interconnected mesh of switching elements. The switching fabric [4] of each of these elements is illustrated in figure 1.

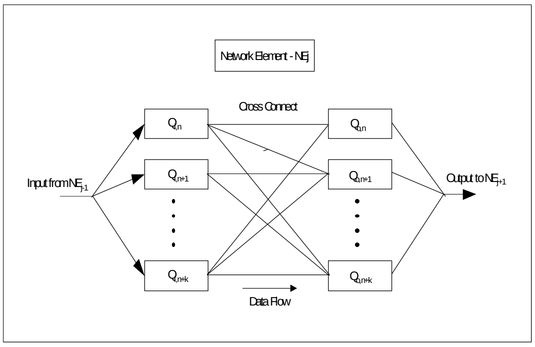

Figure 1 Switching Array

The generic element contains an arbitrary number of fully interconnected input and output queue pairs. The traffic flow between these queues is governed by a set of non-linear signal translation functions [2] which model the traffic flow characteristics of a prioritised switching system exhibiting traffic synchronisation [1].

Traffic arrivals at each element of the simulated network consist of the superposition of an exogenous traffic stream generated with non-uniform probability, and a proportion of the endogenous departure streams from each directly connected neighbouring element. The exogenous stream is tailored to model both peaked-uniform and bursty traffic sequences.

The routing strategy is based on logical paths though the spatial geometry of a network and the behavioural characteristics of the traffic stream are monitored by the control system of each element on the source-destination route.

Given a uniform input traffic stream with peak bursts described by the function

$$u(t) = \overline{m} + f(\overline{m}, t) \qquad (1.1)$$

Where $\overline{m}$ is the mean stable flow and $f(\overline{m}, t)$ is a function of the mean flow relative to time *t*, which represents a peak burst of duration $t + \delta t$. Each peak occurs with a probability $P(f(\overline{m}, t) > 0) = 1/\tau$, where τ is the periodic sample frequency of a peak event.

The general behaviour of a unit generic element under such input conditions is described by the state space analysis, shown in figure 2.

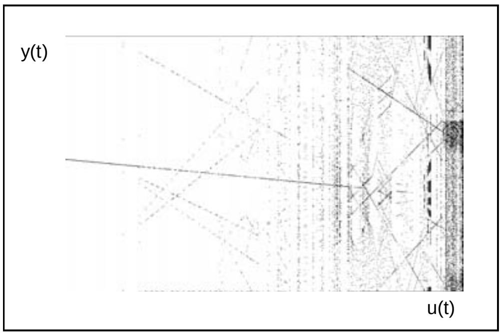

Figure 2 State Space map of unit element output

This map illustrates the fluctuations in stability as the input rate, $u(t)$, is uniformly increased, subsequent to the removal of transient effects. It may be noted that as the input is increased, the traffic behaviour grows increasingly unstable in nature. The uniform linear patterns propagating through the map are an indicator of stable period cycles, whilst the increase in $y(t)$ intensity is a general indication of evolving unstable behaviour.

The effect of cascading this behaviour through five serially connected elements is shown in the state space map of figure 3.

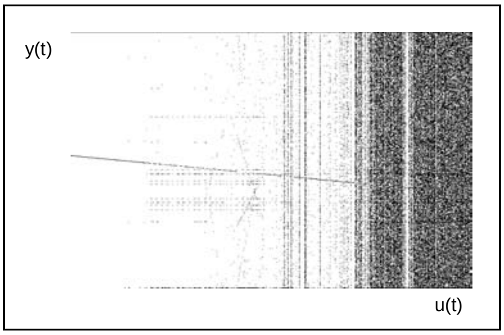

Figure 3 State Space map of cascade output

This analysis illustrates the growth in intensify of the unstable periodic behaviour through the propagation of the traffic signal. The additive cascade function may be expressed as

$$y_n(t) = f(y_{n-1}(t), x_n(t)) \qquad (1.2)$$

, where y_n expresses output signal, x_n the transfer function of the unit element switch and *n* specifies the cascade element.

III. Traffic flow processing

In order to quantify the behaviour of the generic network switching element a method has been devised to monitor dynamic activity present in the traffic stream and produce a quantitative measure which may be utilised by a control mechanism [3].

The method associates a virtual area of the control sub-system memory with each arrival and departure queue present within the switch fabric. The reserved areas are organised as indexed vectors, with each being updated at discrete time intervals during the model simulation. The update consists of applying relationship (1.3) to the mean level of traffic intensity over the measurement interval and incrementing the associated index.

$$v[i] = v[i] + k\,, \quad \text{where } i = \frac{\phi_t}{i_{\mathbf{max}}}\,, \qquad (1.3)$$

i_{max} is the maximum size of vector *v* and ϕ_t is the traffic rate at time instant *t*.

In this manner a moving-window distribution is produced within the vector, directly relating to the dynamic properties of the traffic stream. The distribution is then treated in terms of statistical features, each regarding an aspect of the dynamic activity in order to create a series of coefficients representative of the measurement window.

The vector contents are constantly monitored to ensure that redundant historical data is removed in order to maintain the moving variable sized time-window on the traffic flow evolution. This is achieved by assigning a lifetime to each to each measurement entering the vector. At the time of expiration the data is removed if it is found not to be forming part of the consistent periodic dynamics.

The core statistical features extracted from the distribution data consist of the zero-ratio, the peak count, the entropy and the degree of oscillation. The zero-ratio relates those indexed vector locations containing no data to those containing some data, as described by

$$Z = \frac{\sum_{k=0}^{N} v[k]}{N}, \quad \text{for all } v[k] > 0 \qquad (1.4)$$

The peak count provides the aggregate distinct peaks within the distribution to establish an approximation of the fundamental frequency periodicity present within the traffic stream.

The entropy measurement indicates the degree of disorder within the traffic flow according to equation set (1.5)

$$E = \sum_{k=0}^{N} P_k \ln(P_k),$$

where $$P_k = \frac{v[j]}{\sum_{j=0}^{N} v[j]}. \qquad (1.5)$$

The degree of oscillation measures the number of consistent points of oscillations within the traffic stream to establish whether a regular pattern exists within any detectable periodic behaviour.

Each of these descriptive metrics represent an aspect of the traffic flow distribution window, together forming a general characterisation of the system behaviour. This information is then presented as feature coefficients to a predictive neural mechanism as described in section IV.

Traffic emanating from the generic switching element provides a component view of any dynamic activity generated by the element itself and from endogenous traffic arriving from neighbouring elements. This provides an inferred measurement of activity within each element of the surrounding network locale; and in this manner the overlapping distributed evaluation and control system envelops the entire network.

IV. The Tactical Control Mechanism

The task to be solved by the control mechanism is essentially one of forecasting the temporal evolution of the traffic stream. In order to achieve this, the statistical feature coefficients from the traffic processing stage are presented to the inputs of a recurrent backpropagation neural network, as illustrated by figure 4.

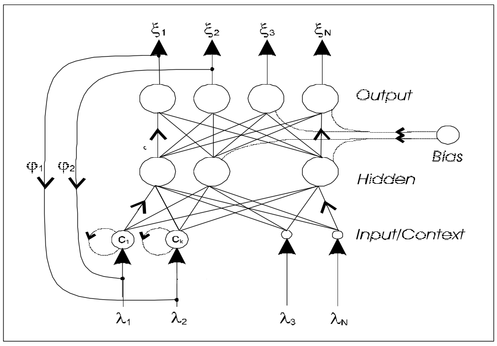

Figure 4 Recurrent Back-Prop Model

The network consists of the standard feedforward model with recurrent context links $,(\varphi_1 \ldots \varphi_N)$, propagating feedback information from the output layer, $(\xi_1 \ldots \xi_N)$, into the input layer, $(\lambda_1 \ldots \lambda_N)$. The context unit, C_i, activation function therefore takes the form

$$C_i = g(C_i) \cdot \sum_{k=0}^{N} \varphi_k, \qquad (1.6)$$

where the function $g(C_i)$ refines the feedback strength of the context link product.

Off-line supervised training of the recurrent network consists initially of the analysis of switch performance under the expected range of load conditions, and the corresponding statistical feature mapping relating to behavioural change.

A sequential training sequence is established from this analysis, with the input vector consisting of temporal statistics and the output, a tactical prediction of future behaviour. The network is trained to form a decision-based mechanism capable of making forecasts of the most likely future traffic behaviour based on current temporal dynamics.

In application, the predictive neural network is capable of monitoring the growth of the vector distribution and thereby search for sign of emerging patterns in the dynamic behaviour. Any patterns detected may indicate a range of situations; from that where stability is seen to be consistent indicating that no adjustments in traffic routing are necessary, to showing that the temporal behaviour is indicating that an extreme situation may arise in the near future and that traffic should be re-routed via alternate paths to pre-compensate.

Information from each vector forecast is subsequently collated by a parent decision process producing an optimal routing solution based on the perceived state of the network and the desired direction of the traffic flow.

Simulation Results And Conclusions

The results presented in this paper are based on a locally interconnected mesh of 100 processing elements, with uniform traffic sourcing incorporating irregular intermittent information bursts.

Figure 5a describes the traffic behavioural activity of an arbitrary element suffering heavy loading conditions, with no control activated. The second figure, 5b, shows traffic flow through the same element subsequent to the control mechanism being activated. The reduction in dynamic activity and therefore instability is evident by comparison.

Figure 6 describes the overall network efficiency in terms of the delay associated with the transmission of traffic from source elements to destination elements. T is described by,

$$T = \frac{\textit{Time taken for message traversal}}{\textit{spatial distance travelled}}$$

Efficiency is clearly improved through the reduction in transmission delay brought about by adaptive routing around potential network bottlenecks.

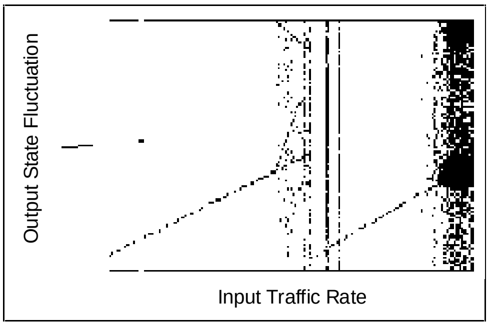

Figure 5a State Space map of sample element output with no control activated.

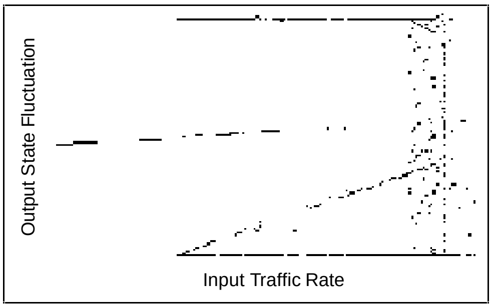

Figure 5b State Space map of sample element output with control mechanism activated.

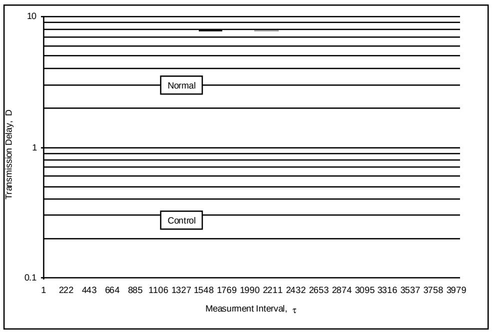

Figure 6 Network efficiency in terms of transmission delay

References

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