Resource Usage Prediction Models for Optimal Multimedia Content Provision

Yiannos Kryftis, *Member, IEEE,* George Mastorakis, *Member, IEEE,* Constandinos X. Mavromoustakis, *Member, IEEE,* Jordi Mongay Batalla, *Member, IEEE,* Joel J. P. C. Rodrigues, *Senior Member, IEEE,* Ciprian Dobre, *Member, IEEE*

***Abstract*—This paper proposes a network architecture that utilizes novel resource prediction models for optimal selection of multimedia content provision methods. The proposed research approach is based on a prototype system, which exploits a resource prediction engine, utilizing time series and epidemic spread models, for optimal and balanced distribution of the streaming data among content delivery networks, cloud-based providers and home media gateways. The proposed epidemic diseases models adopt the characteristics of the multimedia content delivery over the network architecture. In this context, the paper aims to present the advantages of using such models, by presenting and analysing an epidemic spread scheme for Video on Demand (VoD) delivery, to predict future epidemic spread behavior. In addition, the paper presents two algorithms, adopted in the prototype network architecture, for optimal selection of multimedia content delivery methods, as well as balanced delivery load, by exploiting the resource prediction engine. Both algorithms and models are evaluated to establish their efficiency, towards effectively predicting future network traffic demands. The simulation results verify the validity of the proposed approach, identifying fields for future research and experimentation.**

***Index Terms*—Resource Prediction Engine, Content Delivery Networks, Epidemic Spread Models, Quality of Experience, Multimedia Services Systems, Network Architectures, Media Distribution Middleware**

I. Introduction

The work presented in this paper is co-funded by the European Union, Eurostars Programme, under the project 8111, DELTA Network-Aware Delivery Clouds for User Centric Media Events. Part of this work has been partially supported by the Instituto de Telecomunicações, Next Generation Networks and Applications Group (NetGNA), Portugal, and by National Funding from the FCT - Fundao para a Ciência e a Tecnologia through the UID/EEA/50008/2013 Project.

Yiannos Kryftis, Department of Computer Science, University of Nicosia, 46 Makedonitissas Avenue, 1700 Nicosia, Cyprus email: kryftis.y@unic.ac.cy

George Mastorakis, Department of Informatics Engineering Technological Educational Institute of Crete Heraklion, Crete, Greece, email: gmastorakis@staff.teicrete.gr

Constandinos X.Mavromoustakis, Department of Computer Science, University of Nicosia, 46 Makedonitissas Avenue, 1700 Nicosia, Cyprus email: mavromoustakis.c@unic.ac.cy

Jordi Mongay Batalla, National Institute of Telecommunications and Warsaw University of Technology, Szachowa Str. 1, 04-894 Warsaw, Poland, email: jordim@interfree.it

Joel J. P. C. Rodrigues, Instituto de Telecomunicações, University of Beira Interior, Portugal, and University of Salamanca, Spain, email: joeljr@ieee.org

Ciprian Dobre, Faculty of Autonomic Control and Computers University Politehnica of Bucharest 313, Splaiul Independentei, 060042 Bucharest, Romania, email: ciprian.dobre@cs.pub.ro

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GIVEN the tremendous evolution of multimedia-related technologies over the Internet, more pressure is applied for further research and development on the field of multimedia content distribution. A significant part of the global Internet traffic is generated by video and audio on demand services or other multimedia services, while the amount of this traffic is expected to double in the future [1], leading towards the Future Media Internet. Recent advantages in connected media technologies and social networks are the driving forces, while broadband infrastructure growth and cloud computing that has emerged as a new paradigm for hosting and delivering services over the Internet, are the keystones for the upcoming Future Media Internet. The rapidly transforming environment that surrounds the citizens forces them to the demand of more community-centric experiences through networked/connected media and social networks and to even better Quality of Experience (QoE). Media content delivery plays a key role for the QoE, pressing for more research on novel network architectures, as well as the relative components that allow efficient and balanced content delivery. In addition, novel algorithms and models for the prediction of the resources are vital to be adopted for efficient multimedia content provision.

Tackling such challenges, this paper goes beyond the current state-of-the-art, elaborating on a new multimedia services delivery solution. The proposed solution is based on the optimum allocation of the resources used for content transmission to efficiently satisfy different users requests through the exploitation of existing servers infrastructures capabilities. Such capabilities are available in conventional clouds (i.e. public or private computing infrastructure configurations, usually offered by over-the-Top providers) and in Content Delivery Networks (CDNs). Additionally they can be offered by Home Media Gateway Clouds (i.e. Home Gateways/Community Gateways configurations, exploited in peer-to-peer mode). The proposed approach foresees a new business model in multimedia services delivery over the Internet, strongly but smoothly leveraging (in an evolutionary way) new mechanisms and systems. Among others an epidemic spread model is proposed that is proven to accurately describe a Video on Demand (VoD) spread.

In this context, this paper is organized as follows: Section II presents related work on Resource Prediction Engines and on Epidemic Models, as well as the research motivation of this paper. Section III elaborates on the proposed research approach based on a novel network architecture that utilizes a resource prediction engine, an epidemic model and two algorithms for optimal multimedia services provision. Finally, Section IV provides the evaluation results and Section V includes the conclusion of the paper, accompanied with fields for future research.

II. Related Work and Research Motivation

Several existing research attempts elaborate on the combination of different delivery methods, in order to achieve better QoE for the users. In [2] Xu et al. propose a CDN-P2P hybrid architecture for cost-effective streaming media distribution that combines the advantages of using CDN for providing high QoE with the low cost of using P2P-based stream. Yin et al. in [3] present the design and deployment of a Hybrid CDN-P2P System for Live Video Streaming, demonstrating the improvement in startup delay time and in stability. In [4] Ciullo et al. also propose a peer-assisted video distribution in order to reduce the server workload and to introduce scalability to the system. They suggest a stochastic fluid framework that allows the estimation of the needed bandwidth for the satisfaction of the user requests based on predefined scenarios. In an energy-aware approach in [5] Mandal et al. analyzed and presented the advantages of the integration between CDN and P2P networks. Zhang et al. conducted a measurement study on Kankan, that is one of the leading VoD streaming service providers in China and is based on a hybrid CDN-P2P architecture. They present how the provider utilizes the P2P network for storage and streaming of videos, and how the CDN servers assist the streaming procedure [6]. Current research approaches focus on how to benefit from the combination of the different delivery methods but they do not take consideration of handling each resource separately. In comparison to such approaches, our proposed solution goes beyond the current state-of-the-art, by handling each resource (i.e. streaming channel) separately based on the prediction of the future demand for each resource, as well as the predicted network metrics. The early prediction before the actual need provides to the proposed system the ability to enforce management actions to maintain a high quality of experience (QoE) for the users [7], [8].

A resource prediction engine (RPE) constitutes an important part of multimedia content delivery system, in order to offer the desired QoE to the end users [9], [10], [11]. Its role is to provide the ability to efficiently predict the needed bandwidth capacity and the upcoming network fluctuations. The prediction engine has to be based on novel methods and models that can accurately forecast the future demands, in order to trigger through a management plane the proper actions for keeping the desired quality for the streaming sessions. In [12] Niu et al. presents some time-series analysis techniques to predict the server bandwidth demand and the peer upload for content delivery in peer-assisted Video-on-Demand (VoD) services. The analysis includes prediction of future population for each video channel, by analyzing and fitting to existing models, past data about the population of video channels. The seasonal ARIMA (auto-regressive integrated moving average) model [13] is exploited, for avoiding the periodicity. Additionally they use machine learning techniques for inferring the initial population of a new released channel, by utilizing pass data from newly released videos as training data. For the prediction of the server bandwidth demands by a video channel at future time, the ARMA (auto-regressive moving-average) model was used [13]. They prove that the entire procedure has reasonable computation cost. In [14], Niu et al. present a system for VoD providers in the Cloud, that provides the ability to predict the upcoming need for bandwidth in order to auto-scale accordingly. The near future demands expectations are estimated based on the history of demands as monitored by the cloud monitoring services. This provides the opportunity to reserve the minimum bandwidth needed for satisfying the demand in the desired quality. In a similar manner our proposed RPE utilizes a combination of statistical models for the prediction of future needs. The innovation originates from the selection of the appropriate model, out from a pool of statistical models (ARMA [13], ARIMA [13], Theta method [15] and cubic splines [16]), that better describes each content delivery. Additionally the epidemic model proposed by this paper, provides to the RPE the capability to predict sudden and intense increase of delivery need for specific content. For a resource prediction engine able to forecast future demands, the recent advantages in connected media technologies and social networks should be taken into account. Social networks play a significant role in content delivery, by providing ways of interactions among users that can lead to a lightning spread of content [17]. In [18] Gonccalves et al. suggested a probabilistic resource provisioning approach that utilizes the basic susceptible-infectious-recovered (SIR) model, developed for epidemiology spreading, to represent the sudden and intense workload overflow in VoD delivery process. More specifically they use Markov chain to describe the behavior of the users and they trace the cases of epidemic spread, or as the call it buzz effect, by introducing a Hidden Markov Model with two different rates to represent the buzz and buzz-free behavior. Contrary we propose an epidemic model with more states, customized to describe the epidemic spread of content through the proposed overall system. Additionally our suggestion for the prediction is based on fitting historical data into the proposed model. Epidemic model spreading in scale free networks has been intensively studied [19]. In [20] Pastor and Vespignani analyzed data from computer virus infections and they defined a dynamical model for the spreading of infections on scale-free networks. The spread of computer viruses really resembles the epidemic spread of human diseases. In this context, this paper extends the basic disease models, by presenting a novel model that can be used to accurately describe the multimedia content delivery (i.e. VoD delivery) and so it can help forecasting epidemic spread of multimedia content. The majority of disease models are based on a splitting in compartments of the individuals in a population based on their disease status [19], [21], [22], [23]. The basic susceptible-infectious-recovered (SIR) model provides the foundations of almost all mathematical epidemiology. The differential equations that describe the model are the following:

$$\frac{dS}{dt} = b.N - \beta.S.I - d.S \tag{1a}$$

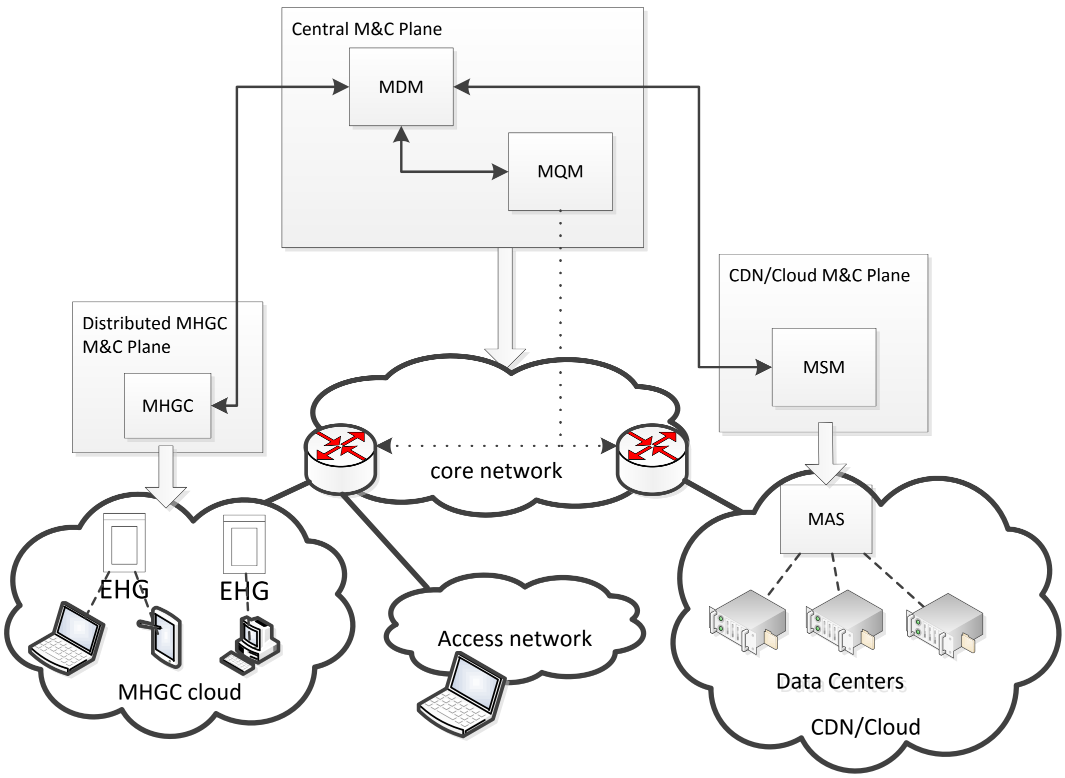


Fig. 1: Proposed Network Architecture

$$\frac{dI}{dt} = \beta.S.I - \delta.I - d.I \tag{1b}$$

$$\frac{dR}{dt} = \delta.I - d.R \tag{1c}$$

$$S + I + R = N \tag{1d}$$

In these equations, S, I and R refer to the number of susceptible, infectious and recovered individuals, respectively, in a population of size N. The other parameters are the birth rate, b, the natural death rate, d, and the rate of recovery from infection, δ. The force of infection, π, is the rate, at which susceptible individuals become infected. It is a function of the number of infectious individuals; this parameter contains information about the interactions between individuals that lead to the transmission of infection. When the population is randomly mixing, the force of infection can be calculated as follows:

$$\pi = \beta.\frac{I}{N} \tag{1e}$$

where β is the effective number of contacts per unit time. This leads to a nonlinear term ($\frac{\beta.S.I}{N}$) representing the transmission of infection, generating a variety of rich dynamical behaviours. Theoretical modelling of how diseases spread in complex networks is based on the assumption that the propagation is driven by reaction processes and that the transmission occurs from every infected neighbouring entity at each time step, producing a diffusion of the epidemics on the network. Possible modifications on the available states of the SIR model, lead to some widely used epidemic models like the susceptible-infectious-susceptible (SIS) model where the recovered state does not exist and individuals are considered immediately susceptible. In the same context the maternally derived immunity-susceptible-infectious-recovered (MSIR) model compared to the SIR model it includes a state for a population born with immune to the disease. In such a model, an additional differential equation is needed to describe the transitions from state M to the state S. This equation takes into consideration the percentage of population with immunity and its lasting period [24], [25]. Similar models have been used in finite-size scale-free networks, for traffic-driven epidemic spread [26], for efficient data streaming [27] and for virus spread in such networks [28]. Also, this approach has been used in the area of multimedia content distribution, [17], in dynamic resource management [18], and for segmented file sharing [29]. Although there is impressive research in epidemic models for use for the description of behaviour of computer networks, there is a lack of a model, able to describe the specific need for multimedia content delivery architectures. Part of this paper is dedicated to an epidemic model for that purpose. Additionally, this paper elaborates on a network architecture that predicts the future content delivery demands and the future network usage, by utilizing novel models and algorithms, performing all the necessary adaptations to deliver the content in an optimal and balanced way for the optimal provision of the desired Quality of Service (QoS) and QoE to the end users.

III. Epidemic Model for Optimal Multimedia Services Provision using a Resource Prediction Engine

A. Network Architecture

The introduction of a Resource Prediction Engine with Epidemic Models utilization, towards the provision of multimedia services, demands a network architecture with management components in different layers that cooperate during the multimedia delivery process, achieving optimal content delivery. The proposed network architecture is shown in Fig. 1. The upper layer is called Central Management and Control (M&C) plane and it coordinates the collaboration environment, by interchanging information with existing M&C planes of the CDN and Cloud providers, as well as the distributed M&C plane of the Media Home Gateway Cloud (MHGC) provider, consisted of user gateways, forming a Peer-to-Peer (P2P) network. The proposed network architecture as presented in Fig.1 consists of the following entities: a Media Distribution Middleware (MDM), a Media QoE Meter (MQM), a Media Services Manager (MSM), an Enhanced Home Gateway (EHG) and a Media Advanced Streamer (MAS). In a bottom to top presentation of components based on the functionality, the EHG entity is part of the home equipment of the end users. The control modules of EHGs constitute the Media Home Gateway Cloud (MHGC) M&C plane and they are responsible for creating the MHGC ad-hoc system from a set of peer-to-peer connected EHGs. Each EHG receives content requests from the users, requesting data from the MDM, about which MHGC peers should get involved to efficiently deliver requested content. EHG collaborates with MSM entities that reside in CDN/Cloud M&C planes and manage all Service Providers resources, to obtain media content requested by the user, if the content is not stored on any of EHGs belonging to given MHGC. The MSM, according to the recommendations received from the MDM, takes a decision on which server should stream the requested media and with which bitrate. In this way, the MSM, contrary to the existing solutions, performs adaptation decision, taking into account not only the available bandwidth, but also considering other important information addressed by the MDM, such as the estimated QoE value and the prediction of the potential upcoming streaming sessions. The MAS entity resides in the CDN/Cloud domain as a standalone component. Its role is to perform the streaming process, according to the instructions received from the MSM/EHG entity. MQM component is responsible for continuous monitoring of network metrics at the users and the Service Providers domain access points, as well as the users context and preferences. Based on the data gathered by the set of the MQM probes, distributed all over the domain, this entity provides to the MDM the related data about the current network conditions and the estimated value of QoE available for a user. Moreover, the MQM sends alerts to the MDM, only if any of the monitored QoS/QoE parameters declines below the allowed level. MDM is the main component of the Central M&C plane. It executes all necessary operations and determines all data required for optimal allocation of the available resources at each Resource Providers domain. As a result, the MDM returns guidelines, which resources should be used for handling given users request, to achieve the best (in terms of efficiency) resource exploitation.

B. Resource Prediction Engine for Optimal Multimedia Services Provision

The MDM adopts a resource prediction engine, in order to be able to predict future demands for resources. The prediction is divided in long-term prediction for future demands for resources and short-term prediction for some important network metrics like throughput. The long-term prediction takes as input the demand for each resource in the past, using a combination of statistical methods and algorithms for the adaptivity to description models, in order to predict future demands. This provides the opportunity to the system to make the optimal distribution of data in Clouds, CDNs and EHGs based on the prediction before the actual need. On the other hand, the short-term prediction is used for predicting and preventing upcoming network congestion issues, by triggering the proper management actions. Fig. 2 presents the internal architecture of the MDM component. The QoS/QoE Politics Traffic Data History component collects and stores the monitoring data delivered from the MQM. It forwards it periodically to the Media Traffic Forecast to generate the prediction for the traffic in the network. The Media Traffic Forecast utilizes the epidemic model for the prediction of the upcoming epidemic or not spread of the content and the time series models for the prediction of future values of the resources. The outcome of the forecasts is used as input to the Resource allocator/scheduler. It uses algorithms that combine the current and predicted values of specific metrics to decide on the optimal delivery methods and the most suitable servers to perform the multimedia content delivery. The results are feeding the MSM component, as recommendations regarding which server should stream the requested media, while at the same time the Bandwidth Allocation Optimizer calculates the optimal bandwidth allocation for the P2P delivery between the MHGC devices. It is an online system, which takes into consideration the network metrics that come from the MQM to decide on the most suitable peers to perform the streaming. It delivers that information directly to the MHGC devices. MHGC devices exchange management information between them and together they constitute a M&C plane that manages the P2P network between the EHG devices. The Adaptivity to resources conditions component ensures that the Bandwidth Allocation Optimizer runs periodically to retain the optimal suggestions based on updated information from the resources and network.

C. Epidemic Models for Prediction of VoD download rate

The paper examines the effectiveness of the epidemic models on the prediction of VoD usage as part of the general issue of optimal content delivery. As shown in 3, the model divides the population into several compartments based on the percentage of the population in each state. The Susceptible (S)

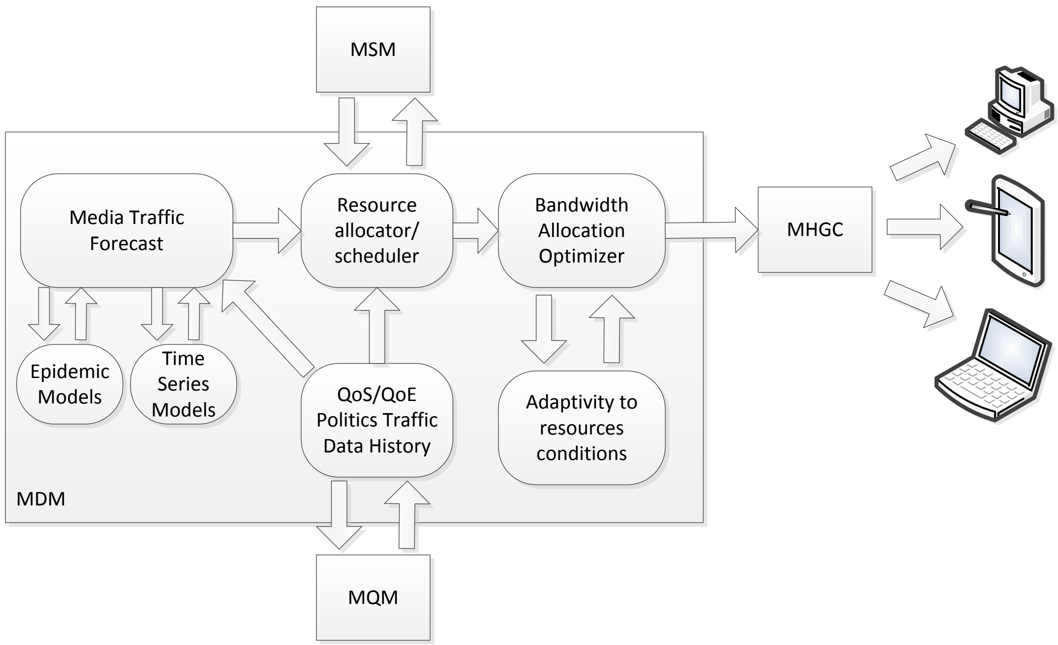


Fig. 2: Media Distribution Middleware Internal Architecture

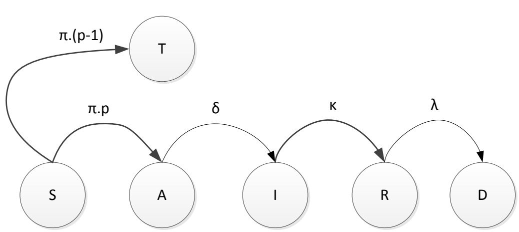


Fig. 3: Epidemic Model for Efficient Multimedia Content Provision

group includes subscribers that can download the Video, the Active (A) includes the users that are currently downloading the Video, the Infected (I) contains the users that downloaded the Video and they can spread it through social networks (if they liked the video), the Recovered (R) contains the Users that passed from the Infected phase but they do not spread the Video any more (after some period of time) while the Deleted (D) group includes users that removed the Video after sometime or the Video was automatically removed from the cache after some period of time. The Turned_down (T) group includes the Users that belonged to the S category and they took the decision to turn down the Video, so they will never download it. In the model, $N_S(t)$, $N_A(t)$, $N_I(t)$, $N_R(t)$, $N_D(t)$, $N_T(t)$, $t \geq 0$, are stochastic processes representing the time evolution of each population.

Suppose there are *n* clients of the VoD provider, they all belong to the group S at time=0, when a VoD is initially uploaded by the provider. The transition rate from state S to A consists of the probability to have a new spontaneous viewer, plus the probability to have some users that learned about the video from their social contacts and they came to a decision to watch the video. So the equation (1e) of the SIR model that expresses the non-linear term of the rate of transmission of infection, can be extended to:

$$\pi(t) = \gamma + \beta.N_S(t).N_I(t) \tag{2a}$$

where β is the social network contact rate for users based on the specific video, and γ is the number of spontaneous viewers that in some cases can be considerable important since a specific VoD may be advertised and promoted by the VoD provider. For the transition from Active state to Infected state there is a need of consideration of the download rate of Users and of length of the Video. Since the Video download is happening directly during viewing and there are mechanisms for balanced delivery the time needed for the transition is considered as a random variable and is expressed as a Poisson process with mean value the duration of the video. The transitions, from Infected to Recovered and from Recovered to Deleted, are also considered as random variables since each user can spread the information to its social network for a random period of time and can also keep the video in in its EHG device again for a random period of time. So for the proposed model, the specific transitions are again described as Poisson processes with mean times the estimations of how long the Users are spreading the information to their social networks and the period that the Video stays in the device of each user. The rates can be expressed as follows:

$$\delta(t) = \frac{1}{videoDuration} \tag{2b}$$

$$\kappa(t) = \frac{1}{SpreadPeriod} \tag{2c}$$

$$\lambda(t) = \frac{1}{KeepInCachePeriod} \tag{2d}$$

This model makes the following assumptions (1) A user that downloads a video will never request it again, (2) There are no changes in user's population/subscribers, (3) Users in T state that turned down the video will never become Susceptible again. The first two assumptions help on making the analysis simpler without losing the generality, since they are well fitting a VoD provider use case. Regarding the first assumption, When a user downloads a video, it remains in its local EHG for a few days. So a re-download is performed only in the case that a user wishes to view it again after that period. This case does not importantly affect the analysis, since the epidemic spread occurs in short periods of time and with the existence of cache it is unlikely to have double downloads during the study of a single epidemic spread incidence. Similarly the second assumption is realistic since the population of the subscribers remains almost constant within such short periods. The third assumption does not really change the analysis, since it is not possible to calculate the population of state T before the actual spread of the Video. In the measurements S and T populations are handled together and they can be separated only in the end of each VoD life cycle. The following equations describe the model:

$$\frac{dS}{dt} = -(\beta.I + \gamma).S \tag{3a}$$

$$\frac{dT}{dt} = (\beta.I + \gamma).S.(1-p) \tag{3b}$$

$$\frac{dA}{dt} = (\beta.I + \gamma).S.p - \delta.A \tag{3c}$$

$$\frac{dI}{dt} = \delta.A - \kappa.I \tag{3d}$$

$$\frac{dR}{dt} = \kappa.I - \lambda.R \tag{3e}$$

$$\frac{dD}{dt} = \lambda.R \tag{3f}$$

$$S + T + A + I + R + D = 1 \tag{3g}$$

Fig.4 presents simulation results executed in Matlab. The aforementioned differential equations were expressed as Matlab equations and the simulation was performed in timesteps. After each timestep part of the population was moving to a different state based on the equations and the rates. In simulation results of Fig. 4 the rates are as follows: $\beta = 0.5, \delta = 0.1, \kappa = 0.01, \lambda = 0.005, p = 0.8$. The whole population belongs to the S state(S=1) when t=0. At $time = 50 timesteps$, the population of Active(A) increases showing that there are active users downloading the Video, while at $time = 70 timesteps$ the population of Infected(I) increases significantly. An important outcome is the final population

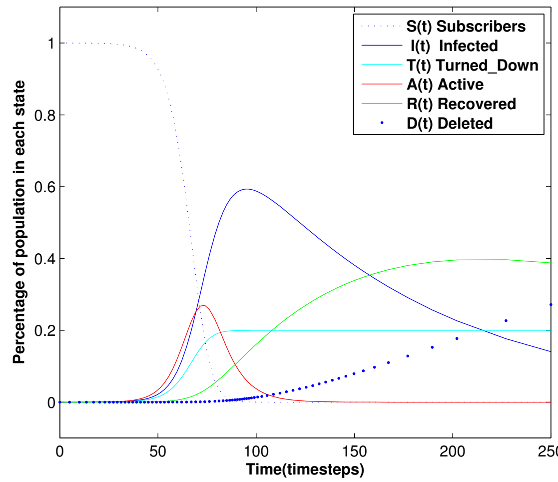


Fig. 4: Percentage of Population in each State

in state Turn Down(T) that tends to $p - 1 = 0.2$ while the population of Deleted(D) tends to $p = 0.8$ as expected since 80% of the population chooses to view the Video. The most important line is the A(t) since it depicts the bandwidth need for covering the needs of the active downloads. It is clear that in case of epidemic spread of a specific Video, the population of simultaneous downloads is significantly increased, something that increases the difficulty in delivering high Quality of Service. A solution to the problem is the use of P2P delivery complementary to the Cloud and CDN delivery. An important observation is that by the time when the Active (A) users introduce a significant increase in their population, there is always an important number of users in Infected (I) and Recovered (R) states that can seed the Video for the them through P2P delivery method. Finally, it is clear that the transmission from Recovered (R) state to Deleted (D) does not affect the needed recovered population when it is most needed.

Lemma 1: if $\gamma > 0$ then

$$\lim_{t->\infty}(T(t) + D(t)) = 1$$

Proof $T(t) = T(t) - T(0) = \int_0^t \frac{dT}{dt}dt$
Since $\frac{dT}{dt} = -(1-p)\frac{dS}{dt}$, we conclude that $T(t) = -\int_0^t (1-p)\frac{dS}{dt}dt = -(1-p)(S(t) - S(0)) = (1-p)(1-S(t))$. Notice that $\frac{dD}{dt} \geq 0$, hence D is increasing. $D(s) \leq 1$ for all s therefore $\lim_{s\to\infty} \frac{dD}{dt}|_s = 0$. Hence, $\lim_{s\to\infty} R(s) = 0$ if we assume $\lambda > 0$. Similarly:

- $\lim_{s\to\infty} \frac{dR}{dt}|_s = 0$, and therefore $\lim_{s\to\infty} I(s) = 0$ (assuming that $\kappa > 0$),
- $\lim_{s\to\infty} \frac{dI}{dt}|_s = 0$, and therefore $\lim_{s\to\infty} A(s) = 0$ (assuming that $\delta > 0$),
- $\lim_{s\to\infty} \frac{dA}{dt}|_s = 0$, and therefore $\lim_{s\to\infty} S(s) = 0$ (assuming that $\gamma > 0$).

Hence, since $S + T + A + I + R + D = 1$, we see that $\lim_{s\to\infty} T(s) + D(s) = 1$ By the equation $T(t) = (1-p)(1-S(t))$, we see that $\lim_{s\to\infty} T(s) = 1 - p$. Hence, we also see that $\lim_{s\to\infty} D(s) = p$.

The outcome of Lemma1 is the fact that in infinite time all the population will finally go to the state T-Turn Down and D-Deleted, given we have $\gamma > 0$. The lemma is useful for the analysis after the end of the content delivery for extracting the percentage of users that turned down the video.

An important metric for the model is the basic reproduction rate of the epidemic R_0 that can be calculated as in (Global analysis of multi-strains SIS, SIR and MSIR epidemic models):

$$R_0 = \frac{p * \beta}{\kappa}$$

Lemma 2: if $R_0 > 1$ then the epidemic cannot maintain itself

Proof If $R_0 > 1$, then on average, each infected individual infects more than one other member of the population and a self-sustaining group of infectious individuals will propagate. If $R_0 < 1$, then the epidemic cannot maintain itself because each individual, on average, infects less than one member of the population.

The estimation of R_0 is not easy before the actual spread of the VoD because the β value is not easy to be predicted, since the social impact of each VoD is different. An estimation can be done based on some of the Video properties, (category, actors, director etc) and some history data, but this is out of the scope of the specific paper.

It is interesting to study and compare the model in the case where there is no epidemic spread($R_0 < 1$). To simplify the analysis it is safe to say that if there is no epidemic spread it can be considered that $\beta = 0$. In this case the Infected(I) and Recovered(R) population are in the same state Captured(C). The equations are transformed in the following:

$$\frac{dS}{dt} = -\gamma.S \tag{4a}$$

$$\frac{dT}{dt} = \gamma.S.(1-p) \tag{4b}$$

$$\frac{dA}{dt} = \gamma.S.p - \delta.A \tag{4c}$$

$$\frac{dC}{dt} = \delta.A - \lambda.C \tag{4d}$$

$$\frac{dD}{dt} = \lambda.C \tag{4e}$$

$$S + T + A + C + D = 1 \tag{4f}$$

By solving the first order differential equations for S and A with consideration that $S(0) = 1$ and $A(0) = 0$ the outcome is:

$$S(t) = e^{-\gamma.t} \tag{5a}$$

$$A(t) = \frac{\gamma.p}{\delta - \gamma.p}(e^{-\gamma.t} + e^{-\delta.t}) \tag{5b}$$

Fig.5 presents simulation results when the rates are as follows: $\delta = 0.1, \kappa = 0.01, \lambda = 0.005, p = 0.8$. The difference it is obvious since the Active(A) population remains very low through the whole delivery process. If we consider that the system is able to deliver simultaneously to up to a specific percentage of Users, then the value of γ can be modified. The VoD provider is able to manage the advertise, or the position in the menu of each VoD and so it can modify the γ value of the spontaneous Users.

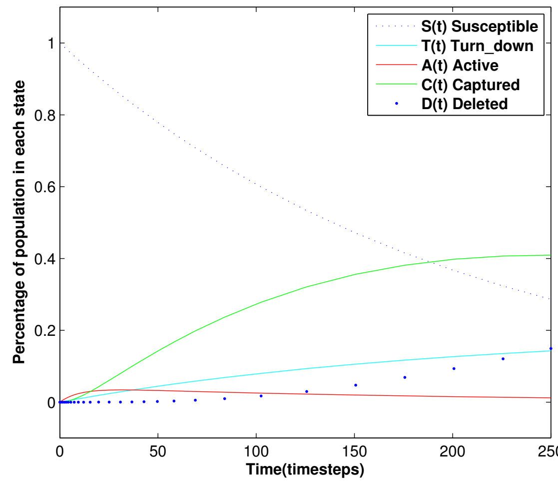


Fig. 5: Simulation Results without Epidemic Spread

Lemma 3: Prediction based on the model. If the A(t) is exponential then it is epidemic, if the A(t) is polynomial then it is not epidemic. In case of predicting an epidemic spread of the Video the algorithm is modified.

Proof In model with epidemic spread
$\frac{dA}{dt} = (\beta.I + \gamma).S.p - \delta.A \approx \beta.I.S.p$
In model without epidemic spread
$\frac{dA}{dt} = \gamma.S.p - \delta.A \approx \gamma.S.p$
The multiplication of S and I populations is what causes the epidemic spread. An early perception of such behaviour could give a benefit the content delivery system.

D. Resource Prediction Algorithms with Use of Epidemic Models

An internal view of the implementation architecture of the prediction engine as part of the Media Traffic Forecast is presented in Fig. 6. Input comes from the Monitoring Service and more specifically the MQM through the QoS/QoE Politics Traffic Data History component. The prediction engine is implemented in Java and it is divided in two parts based on the functionality concerning Time Series Models and Epidemic Models. For the implementation of time series models, there is a use of the JRI, Java Interface [30] for the interactions with the R-system [31]. R is a very popular free software environment for statistical computing and graphics. The standard stats package of R-system includes multiple time series models and prediction methods. The forecast package [32], [33] of R implements automatic forecasting with multiple methods, including ARIMA models, exponential smoothing methods, Theta method [15], cubic splines [16] and many others. Hyndman and Khandakar in [33] present the implementation of exponential smoothing methods and the ARIMA modeling approach in the forecast package. The proposed prediction engine uses the aforementioned packages, extending them in order to achieve optimal prediction. If a long-term (i.e. for the next days) prediction has to be achieved for the needed bandwidth of a specific Video On Demand (VoD), the prediction engine needs to exploit the history of the bandwidth reservation for the specific VoD. The history data is utilized for fitting in the proper statistical model, suitable for the specific VoD and then the forecast function performs the prediction. The result is the estimation of the need of bandwidth for the specific VoD after one hour. This value feeds the Resource allocator/scheduler to decide how to serve the estimated future need. The epidemic model is implemented in Java. It examines the history data behaviour to conclude if it resembles the exponential function something that would predict that the VoD spreads with epidemic speed based on lemma3. The MDM component uses the predicted future values for the metrics, in order to take the decisions for delivery of requested media, which may be streamed: 1) directly from the Cloud, 2) through deployed surrogate servers of the CDN, 3) by establishing a Media Home Gateway Cloud (MHGC) ad-hoc system and using a combined P2P-based technology of distribution with multi-source, multi-destination congestion control algorithms, or 4) a combination of parts or all of them (thanks to stream-switching adaptation technique). The results are forwarded to the MSM component that is responsible for the actual streaming of the data to the user. The selection algorithm is presented below. Algorithm 1 gets as input the current and predicted bandwidth needed for the delivery of specific content over the system and triggers the proper mechanisms to accomplish it in an optimal way. The **neededBW** variable that represents the expected needed bandwidth for the overall delivery of a specific VoD, takes the higher value among the current and the predicted bandwidth need as calculated by the prediction engine. The **epidemicSpread** boolean variable, is assigned a TRUE or FALSE value based on the behaviour similarity to the exponential function, that indicates an epidemic spread (lemma3). If $epidemicSpread = TRUE$ then the algorithm uses all delivery methods simultaneously and it informs the VoD provider to reduce the advertisement of the specific VoD. If $epidemicSpread = FALSE$ it makes the selection based on preset thresholds for bandwidth usage, based on administrative high level decisions and network status. If **neededBW** is below the low threshold, only the Cloud delivery will be used. If it is above, CDN servers will be used. The number of CDNs to be used is defined as a percentage of the available servers, based on the distance of **neededBW** from the low and high threshold. After the high threshold is reached, a P2P delivery method is exploited. This algorithm provides the advantage that the data is not distributed before the actual need. In the case of a VoD with low customers demand, the CDNs will not been used for its distribution. On the other hand, if a VoD becomes viral and it is spreading epidemically, an early prediction will occur, that will allow to use all the available delivery methods to distribute the VoD will rapidly. Finally, the P2P delivery method will be used, only when needed, while at the time that this happens, the number of the users already possessing the specific video will be satisfactory with those users, acting as seeders to distribute the VoD to the others.

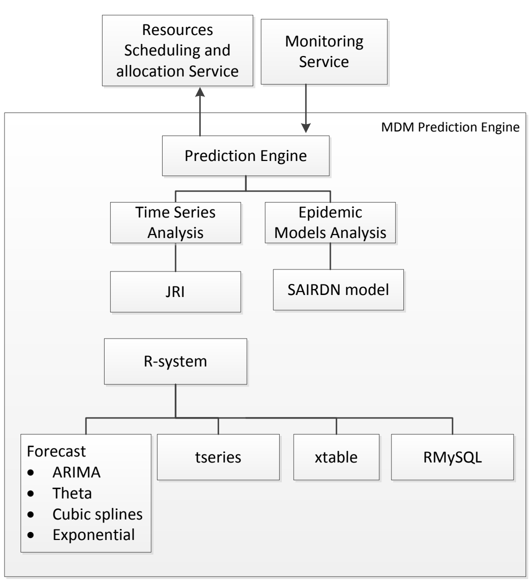


Fig. 6: Implementation Architecture of the Resource Prediction Engine

Algorithm 1 Delivery Method Selection Algorithm

procedure SELECTCONTENTDELIVERYMETHODS
  neededBW ← maximum(currentBW,predictedBW)
  epidemicSpread ← fits(exponentialFunction)
  if $epidemicSpread = TRUE$ **then**
    Use Cloud, all available CDNs and P2P
    Reduce the VoD advertisement
    Run the load balancing algorithm for DCs
  else
    switch $neededBW$ **do**
      case $neededBW < lowThreshold$
        Use only Cloud.
      case $lowThreshold < neededBW < highThreshold$
        $NoOfDCstoUse \leftarrow \frac{neededBW - lowThreshold}{highThreshold - lowThreshold} * AvailDCs$
        Use Cloud and NumberOfDCstoUse DCs.
        Run the load balancing algorithm for DCs
      case $neededBW > highThreshold$
        Use Cloud, all available CDNs and P2P.
        Run the load balancing algorithm for DCs

The aforementioned load balancing algorithm for the load balancing among Data Centers is presented below. Algorithm 2 takes as input the table $W[x, y]$ that includes the workload of each VoD on each Data Center (DC) and the number of DCs to be used for the specific content delivery. It updates

Algorithm 2 Load Balancing Algorithm

procedure LOADBALANCING
  portion ← *1 /* ***NoOfDCsToUse***
  if VoD=new **then**
    Add a column to the W[x,y] table
  column = *Column that represents the current VoD*
  Create a sorted table with the rows, based on the number of 0 they include
  *W[x,column]=****portion****, where x takes the first* ***NoOfDCsToUse*** *values of the sorted table*

the table and returns it with the new values to be used for the balanced distribution of the content. The algorithm divides number 1 (the whole percentage) to the number Data Centers (DCs), which will be used, to calculate the portion of delivery requests that each DC should handle. Then, it finds out which column represents the specific VoD, if it already exists, or it assigns a new column for a new VoD. Finally, it selects which DCs will be used, starting with those that have more zero values in their row, meaning that they do not serve many VoD channels.

IV. Performance Evaluation Analysis and Experimental Results

This section demonstrates the ability of the epidemic models to describe the spread of content over content delivery systems, and the effectiveness of the Resource Prediction Engine to predict future values of network metrics of the utilization of network paths. The effectiveness of the whole proposed system, is demonstrated by simulations of the usage scenarios. Finally this section makes a comparison of the ability of the proposed epidemic model, that was specially designed for describing content delivery, to make an early prediction of an upcoming epidemic spread of content compared to other general purpose epidemic models. The monitoring data was collected by a VoD platform [34] and all the videos had a resolution of 480p.

For the evaluation of the forecast algorithms for the short-term prediction, the monitoring data of the bandwidth usage for serving the need of a specific VoD, was utilized. The collected measurements were for a total of 30 minutes with a period of 5 seconds, but to avoid periodicity of data, the mean value per minute was used. The 80% (24 minutes) of the data was exploited to feed the prediction engine. The RPE as described in section III-D fits the data into the most suitable model and it manages to perform a prediction for the future values. The remaining 20% of the data is then used for the evaluation, through a comparison between the predicted and the actual value as shown in 7. The important part of the graph is after the 24 first minutes, where it is clearly depicted that the measured values remain very close to the predicted ones.

The prediction performance of the RPE is presented in 8. It includes the predicted value showing also the limit of 95% confidence and the corresponding (after the time passes) measured values of bandwidth needs for a VoD channel. The

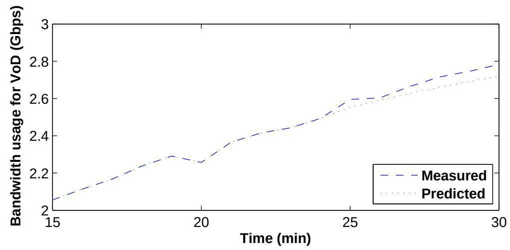


Fig. 7: Measured vs Predicted Value for the Bandwidth Usage for VoD

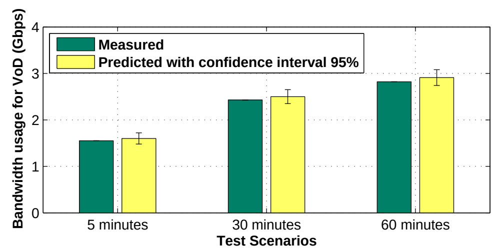
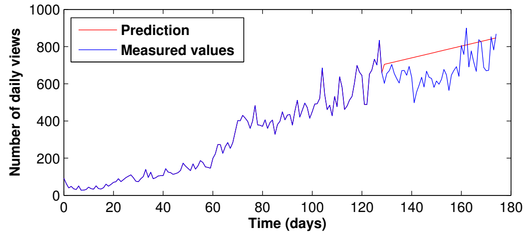


Fig. 8: Test Scenarios for Bandwidth Usage of VoD Prediction

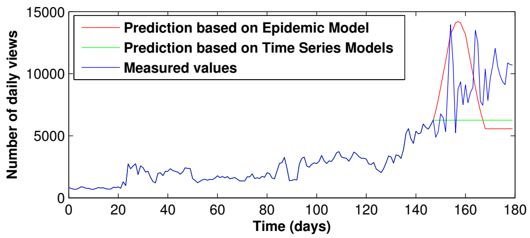
test scenarios presented are for 5, 30 and 60 min prediction. It is clear that the predicted values are near the actual values measured and in all cases the upper and lower limits of the 95% confidence interval include the measured value.

For the evaluation of the long-term prediction models we collected the number of views per day for two videos provided by a VoD platform [34]. The collected data is for 175 days. The 80% of the data was exploited to feed the prediction engine, while the rest of the data was used for the evaluation through a comparison between the predicted and the actual value as shown in Fig. 9. In the delivery of the first video, as shown in Fig. 9a, the time series models are able to predict future demands with enough accuracy. In the second video delivery, as shown in Fig. 9b, the time series models are incapable to predict the upcoming enormous increase of the demand since the measured data did not fit well in any time series model. The prediction based on the time series models forecasted a steady number of viewers that was proven to be wrong. The prediction based on the epidemic model managed to forecast the upcoming epidemic spread and the predicted values are close to the measured values. So the advantage of using algorithm 1 is depicted since the algorithm tries to fit the epidemic models and then if there is no epidemic spread it utilizes the time series models.

For the evaluation of the ability of the proposed epidemic model to make early prediction of an epidemic spread of content through a VoD platform we compare its performance with that of some general purpose epidemic models. The comparison involves our proposed epidemic model, that was specifically designed for describing the spread of content and presented in section III-C, the basic SIR model as described in detail in section II and the MSIR model [25]. We collected from a VoD platform history data for seventeen videos that we consider as viral because they had a peak demand of more than 10% of the total subscribers as simultaneous viewers. The data



(a) An average video



(b) A video that spreads epidemically

Fig. 9: Measured and Predicted number of views per day

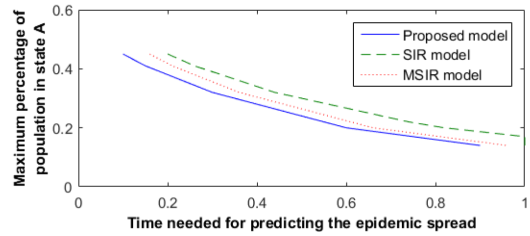
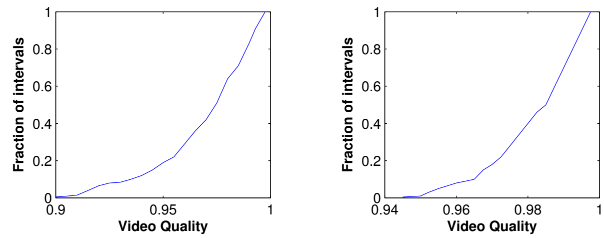


Fig. 10: Time needed for the Prediction of the Epidemic Behaviour



(a) Without the MDM (b) With the MDM

Fig. 11: Fraction of intervals of QoE

about each Video includes measurements about the number of users that were downloading the Video each moment, and so we managed to divide them into the basic compartments of the three models. In each model a number of variables can get values under some constrains. We extended the forecast package of R-system [33] to represent these models and we used a function that automatically assigns values to the variables to fit in the model based on the history data. The amount of data needed in order to deduce that the data can be fitted in the model reveals the time when the actual prediction will be possible in real time. Fig. 10 presents the needed time to predict the epidemic spread, as a percentage of the total lapse time from the release of the video until reaching the maximum value of simultaneous users, for multiple maximum values of simultaneous users based on the seventeen videos of the sample. The graph clearly depicts that all models are able to predict the epidemic spread and in case of a high epidemic spread the prediction is early. In all cases the proposed model has better results since it makes an earlier prediction. The SIR model does not perform very well possibly because of the lack of the needed states to represent accurately the content delivery process. MSIR model performs well, possibly because it has the state M (maternally derived immunity) that corresponds to the state T (Turn-down) state of the proposed model. It performs worse than the proposed model since it does not distinguish the Active users with the Infected, nor the Recovered to the Deleted. The proposed model, provides more variables for customization, and it can be customized to represent the process of content delivery more accurately.

A metric with significant importance in the content delivery process is the Quality of Experience (QoE) for the users. In [3] Yin et al defined quality metrics taking into consideration the time spend in buffering a video compared to the total viewing time to conclude about the QoE. They managed to present results with mean value for the quality metric greater than 0.99 with all measures greater than 0.95. In our approach and since we have a complete network architecture, the MQM component is able to calculate the QoE based on specific dynamical algorithms [35]. The algorithms combine TCP-, buffer-, and media content-related metrics as well as user requirements and expectations to extract a value in the range 0 to 1, that describes the QoE for each video stream. The closest to 1 implies the highest quality. We collected monitoring results for a specific popular VoD two days with normal demand. The first day the MDM was disabled and none of its functionalities were used. As shown in Fig. 11 the fraction confidence interval of QoE for the users when the MDM is not utilized is higher than 0.90 while the mean value is about 0.99. In the second day when we had the utilization of MDM, the QoE remains over 0.94 for all cases with an average of 0.999.

The rest of the section presents experimental simulation results for evaluation of the performance and the offered reliability in streaming activities, offered by the proposed system. Towards implementing such scenario, a common look-up application service for video streaming is set in each node, to enable nodes requesting a stream from a certain user. Fig.12 shows that the number of the participating nodes is increasing, when MDM-enhancing broadcasting is used, instead of a generic broadcasting. This indicates the enhancement that has been done by the MDM in the broadcasting process, whereas the Community Streaming factor W, as introduced in [36], indicates the level of robustness in receiving neighboring feedback during the process of streaming. The total delay time with the number of simultaneous transmissions is shown in Fig.13. The total measured delay is significantly reduced in the presence of MHGC (P2P delivery), whereas the utilization of the existing infrastructure increases the overall delays when multiple transmissions take place

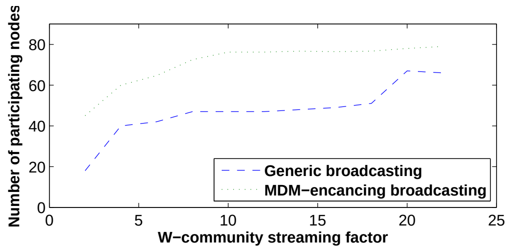


Fig. 12: Number of Participating Nodes with Community Streaming Factor

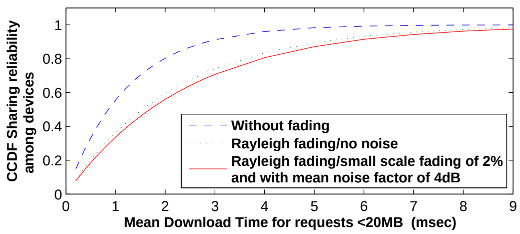


Fig. 13: CCDF Sharing Reliability among Devices with Download Time (msec) for Requests < 20 MB

V. Conclusion

This paper presents a novel network architecture, a novel epidemic spread model and two algorithms for optimal selection of content delivery methods. The proposed epidemic model was analysed and it was shown through simulation results that it can describe the VoD process when the social interactions among users are high for the specific VoD. Based on the analysis we were able to perform prediction for the VoD spread based on the model. The paper also presents two algorithms that take advantage of epidemic models prediction and time series analysis prediction for selecting the optimal delivery method and for load balancing between data centers. The experimental results prove that the prediction engine is accurate and overall the content delivery process gets benefits from the utilization of the model and algorithms. Future directions in our on-going research encompass the further study of the epidemic model for the export of multiple predicted metrics that could be utilized by algorithms for a more accurate forecast of the need or even a better localization of the demand.

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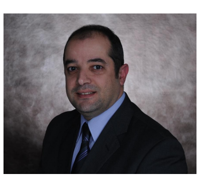
Yiannos Kryftis holds a graduate degree in Electrical and Computer Engineering from National Technical University in Athens. He also holds an MSc in Advanced Computing from Imperial College in London. He is a Phd candidate in National Technical University in Athens with subject Management Architectures and Systems for Future Internet Networks. Currently he is working as a Researcher at the Department of Computer Science at the University of Nicosia. His research interests include Policy-based Network Management, Network Architectures for the Future Internet, Virtualization Information Models and Algorithms in Federated Environments, and Multimedia Services Provisioning.

George Mastorakis received his B.Eng. (Hons) in Electronic Engineering from UMIST, UK in 2000, his M.Sc. in Telecommunications from UCL, UK in 2001 and his Ph.D. in Telecommunications from University of the Aegean, Greece in 2008. He is serving as an Assistant Professor at Technological Educational Institute of Crete and as a Research Associate in Research & Development of Telecommunications Systems Laboratory at Centre for Technological Research of Crete, Greece. His research interests include cognitive radio networks, networking traffic analysis, radio resource management and energy efficient networks. He has a more than 100 publications at various international conferences proceedings, workshops, scientific journals and book chapters.



Constantinos X. Mavromoustakis is currently an Associate Professor at the Department of Computer Science at the University of Nicosia, Cyprus. He received a five-year dipl.Eng (BSc/BEng/MEng, KISATS approved) in Electronic and Computer Engineering from Technical University of Crete, Greece, MSc in Telecommunications from University College of London, UK, and his PhD from the department of Informatics at Aristotle University of Thessaloniki, Greece. Dr. Mavromoustakis is leading the Mobile Systems Lab. (MOSys Lab., http://www.mosys.unic.ac.cy/) at the Department of Computer Science at the University of Nicosia. Dr. Mavromoustakis has extensive experience in simulation of wireless systems, MP2P and Opportunistic Systems, Mobile Computing and Web technologies. He serves as an Associate editor International Journal of Communication Systems (IJCS), Wiley, and editorial board member of the Simulation Practice and Theory (SIMPAT) Journal, Elsevier and as member of Technical Program Committees for various International Conferences.

Jordi Mongay Batalla received his M.Sc. degree from Universitat Politecnica de Valencia (2000) and Ph.D. degree from Warsaw University of Technology (2009), where he still works as an assistant professor. In the past he worked at Telcordia Poland (Ericsson R&D), and he is now with the National Institute of Telecommunications, where, since 2010, he is head of the Internet Architectures and Applications Department. His research interest focuses mainly on Quality of Service/ Quality of Experience in IPv4/v6 and SDN infrastructures, especially multimedia adaptive streaming, Future Internet architectures (Content Aware Networks, Information Centric Networks, architectures for NFV) as well as applications for Future Internet (Internet of Things, Smart Cities, IPTV). He is author or co-author of more than 100 papers published in books, and international and national journals and conference proceedings and editor/ TPC member of several journals and conferences.

Joel J. P. C. Rodrigues is a professor in the Department of Informatics of the University of Beira Interior, Covilh, Portugal, and researcher at the Instituto de Telecomunicaes, Portugal. He received the Habilitation in computer science and engineering from the University of Haute Alsace, France, a PhD degree in informatics engineering, an MSc degree from the University of Beira Interior, and a five-year BSc degree (licentiate) in informatics engineering from the University of Coimbra, Portugal. His main research interests include sensor networks, e-health, e-learning, vehicular delay-tolerant networks, and mobile and ubiquitous computing. He is the leader of NetGNA Research Group (http://netgna.it.ubi.pt), the Chair of the IEEE ComSoc Technical Committee on eHealth, Steering Committee member of the IEEE Life Sciences Technical Community, Member Representative of the IEEE Communications Society on the IEEE Biometrics Council, and officer of the IEEE 1907.1 standard. He is the editor-in-chief of the International Journal on E-Health and Medical Communications, the editor-in-chief of the Recent Advances on Communications and Networking Technology, the editor-in-chief of the Journal of Multimedia Information Systems, and editorial board member of several journals. He has been general chair and TPC Chair of many international conferences, including IEEE ICC and GLOBECOM. He is a member of many international TPCs and participated in several international conferences organization. He has authored or coauthored over 400 papers in refereed international journals and conferences, a book, and 3 patents. He had been awarded several Outstanding Leadership and Outstanding Service Awards by IEEE Communications Society and several best papers awards. Prof. Rodrigues is a licensed professional engineer (as senior member), member of the Internet Society, an IARIA fellow, and a senior member of IT, ACM, and IEEE.

Ciprian Dobre , PhD, has scientific and scholarly contributions in the field of large scale distributed systems concerning mobile applications and smart technologies to reduce urban congestion and air pollution (TRANSYS), context-aware applications (CAPIM), opportunistic networks and mobile data offloading (SPRINT, SENSE), monitoring (MonALISA), high-speed networking (VINCI, FDT), Grid application development (EGEE, SEE-GRID), and evaluation using modeling and simulation (MONARC 2, VNSim). These contributions led to important results, demonstrating his qualifications and potential to go significantly beyond the state of the art. Ciprian Dobre was awarded a PhD scholarship from California Institute of Technology (Caltech, USA), and another one from Oracle. His results received one IBM Faculty Award, two CENIC Awards, and three Best Paper Awards (in 2013, 2012, and 2010). The results were published in 6 books, 10 chapters in edited books, 34 articles in major international peer-reviewed journal (19 as main author, cumulated impact factor of 13.24), over 100 articles in well-established international conferences and workshops (with over 200 citations).