

UNIVERSITI SAINS ISLAM MALAYSIA
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WiMAX TRAFFIC FORECASTING BASED ON ARTIFICIAL
INTELLIGENCE TECHNIQUES

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ABSTRAK

Kebolehan untuk meramal trafik di rangkaian WiMAX merupakan satu ciri yang penting bagi menganalisa prestasinya. Ia mempunyai pelbagai aplikasi seperti penambahbaikan pengurusan rangkaian dan kemasukan data. Tambahan pula, ramalan trafik memainkan peranan yang penting dalam memastikan kualiti perkhidmatan sentiasa kekal pada tahap yang diperlukan. Oleh itu, model ramalan trafik WiMAX baharu yang dicadangkan dalam kajian ini akan meramal trafik menggunakan rekod data trafik (TRD) melalui kaedah Rangkaian Neural Buatan (ANN), K-Jiran Terdekat (KNN) dan Siri Masa Kabur (FTS). Data yang digunakan dalam kajian ini diperolehi daripada rangkaian Libya Max (WiMAX technology) yang dikumpul oleh syarikat Telekom Libya dan Teknologi (LTT) selama 180 hari. Ia merangkumi data bagi bilangan maksimum pengguna atas talian, bilangan minimum pengguna atas talian, trafik MIMO-A dan trafik MIMO-B. Kualiti ramalan trafik WiMAX tertumpu kepada rekabentuk kecerdasan buatan (AI) dengan membandingkan pelbagai konfigurasi dan model-model berlainan topologi dan algoritma pembelajaran. Keputusan mengubah senibina AI adalah berdasarkan kepada objektif untuk memperoleh model AI yang terbaik bagi model ramalan aliran trafik. Konfigurasi yang berbeza telah diuji dengan menggunakan data trafik sebenar yang tersimpan di stesen pangkal (A, B, dan AB) kepunyaan Rangkaian WiMAX Libya. Pengukuran ramalan secara statistik telah digunakan bagi menilai konfigurasi AI yang berbeza dalam memilih model yang terbaik berdasarkan prestasi tertinggi. Hasil kajian mendapati bahawa model KNN yang menggunakan bilangan pengguna maksimum dan minimum sebagai input telah memberikan keputusan yang baik dan tepat bagi purata kuasadua ralat (MSE) dalam meramal trafik secara keseluruhan.

ABSTRACT

The ability to predict the traffic of a particular WiMAX network is crucial in analyzing its performance. It bears various applications in reality, such as enabling better network management and admission. Furthermore, traffic forecasting plays a vital role in ensuring that the quality of service is maintained at the necessary level. Therefore, in this research, a new model for WiMAX traffic forecasting system for predicting traffic time series based on the traffic data recorded (TRD) using Artificial Neural Network (ANN), K-Nearest Neighbor (KNN) and Fuzzy Time Series (FTS) was proposed. The data used in this work are available from LibyaMax network (WiMAX technology) automated by Libya Telecom and Technology (LTT) over a period of 180 days which consist of maximum online user, minimum online user, traffic of MIMO-A and traffic of MIMO-B. The quality of forecasting WiMAX traffic was obtained by focusing on the Artificial Intelligence (AI) design through comparison of different configurations and models that consist of different topologies and learning algorithms. The decision of changing the Artificial Intelligence (AI) architecture is essentially based on the objective to obtain the best AI model for a flow traffic prediction model. Different configurations were tested using real traffic data recorded at base stations (A, B and AB) that belong to a Libyan WiMAX network. Statistical measurement was used to evaluate different AI configurations to select the best model based on higher performance result. The outcome of the study indicates that KNN model using maximum and minimum online user as inputs give good and accurate mean square error results (MSE) in predicting traffic as a whole.

ملخص البحث

القدرة على تنبؤ حركة المرور من شبكة واي ماكس معينة أمر بالغ الأهمية في تحليل أدائها. لأنها تتحمل مختلف التطبيقات في الواقع، مثل تمكين إدارة وقبول أفضل للشبكة. وعلاوة على ذلك، التنبؤ المروري يلعب دوراً حيوياً في ضمان جودة الخدمة والحفاظ على المستوى المطلوب. ولذلك، في هذا البحث، نموذج جديد للواي ماكس لنظام التنبؤ للتنبؤ بالسلاسل الزمنية لحركة المرور على أساس تسجيل بيانات الحركة المقترحة باستخدام الشبكة العصبية الاصطناعية و السلاسل الزمنية الضبابية لأقرب جار. البيانات المستخدمة في هذا العمل متاحة من شركة ليبيا للاتصالات والتقنية (ليبيا ماكس) علي مدي 180 يوم . التي تتألف من الحد الأقصى والحد الأدنى للمستخدم على الإنترنت . للحصول على نوعية حركة المرور التنبؤ واي ماكس من خلال التركيز على تصميم الذكاء الاصطناعي من خلال المقارنة بين التكوينات والنماذج المختلفة والتي تتكون من طوبولوجيا مختلفة وخوارزميات تعليمية. و أساساً يستند هذا القرار علي تغير بنية الذكاء الاصطناعي للحصول علي أفضل نموذج لحركة التدفق ثم اختبار تكوينات مختلفة باستخدام بيانات حركة المرور الفعلية المسجلة في المحطات (أ , ب , أب) التي تنتمي الي شبكة واي ماكس ليبيا . وقد استخدم القياس الاحصائي لتقييم تكوينات مختلفة لأختبار أفضل نموذج يقوم علي اعلي نتيجة في الأداء .

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LIST OF ABBREVIATIONS AND SYMBOLS

| | |
|-----------|---|
| AI | Artificial Intelligence |
| ANFIS | Adaptive Neuro Fuzzy Inference System |
| ANN | Artificial Neural Network |
| ARIMA | Autoregressive Integrated Moving Average |
| ASN GW | Access Service Network Gateway |
| BE | Best Effort |
| BS | Base Station |
| CSN | Connectivity Service Network |
| ertPS | Extended Real Time Polling Service |
| F(A,B,AB) | The function model |
| FTS | Fuzzy Time Series |
| IEEE | Institute of Electrical and Electronics Engineers |
| KNN | K nearest Neighbor |
| LM | Levenberg-Marquardt |
| Meff | Model Efficiency |
| MS | Mobile Station |
| MSE | Mean Square Error |
| nrtPS | Non-Real Time Polling Service |
| PMP | Point to Multipoint Topology |
| PTP | Point to Point |
| QOS | Quality of Service |
| RMSE | Root mean square Error |
| rtPS | Real Time Polling Service |
| SCG | Scaled Conjugate Gradient |
| SDLC | Systems Development Life Cycle |
| SS | Subscriber Station |
| ST | Subscriber Terminal |

| | |
|-----|--|
| T | Represents the WiMAX traffic from MIMO-A, MIMO-B and MIMO-AB users |
| UGS | Unsolicited Grant Service |
| VAR | Variance |
| x / | Normalized values |

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