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Machine learning algorithm estimation and comparison of live network values of the inputs which have the most effect on the FEC parameter in DWDM systems

DWDM sistemlerinde FEC parametresine en çok etki eden girdilerin canlı ağ değerlerinin makine öğrenimi algoritması tahmini ve karşılaştırılması

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DWDM Sistemlerinde FEC Parametresine En Çok Etki Eden Girdilerin Canlı Ağ Değerlerinin Makine Öğrenimi Algoritması Tahmini ve Karşılaştırılması

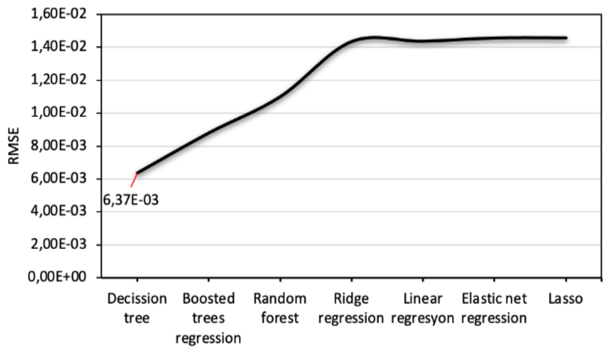
Machine Learning Algorithm Estimation and Comparison of Live Network Values of the Inputs Which Have the Most Effect on the FEC Parameter in DWDM Systems

Highlights

- *Canlı Network Değerleri ile Çalışma/Working with Live Network Values*
- *FEC Değerine Etki eden En Önemli Girdiler/The Most Important Inputs that affect the FEC Value*
- *En Etkili tahminleme yapan Makine öğrenme Algoritması/The most efficient predictive machine learning algorithm*
- *Uçtan uca üretici bağımsız analiz/End to end analysis with vendor agnostic*

Graphical Abstract

Comparison of 7 different machine learning and live network values.



Şekil /Figure

Aim

FEC değerini etkileyen girdilerin makine öğrenme metodu ile tahminlemesi./ Prediction of inputs affecting FEC value by machine learning method.

Design & Methodology

7 farklı makine öğrenme metodu ile 945 adet canlı network üzerinden alınan link analiz edilmiştir./ 945 Links received over live networks were analyzed with 7 different machine learning methods.

Originality

Uçtan uca üretici bağımsız analizler canlı network değerleri ile yapılmıştır./Analyses is made end-to-end with live network values and is vendor agnostic.

Findings

FEC değerine etki eden en önemli parametreler ile en etkili tahminleme yapan makine öğrenme algoritması gözlenmiştir. / It has been observed that the most important inputs affecting the FEC values and machine learning method.

Conclusion

En etkili makine öğrenme metodunun decision tree algortiması olduğu ve FEC değerine etki eden en etkili 3 parametrenin ise fiber zayıflama , link sayısı ve kanal sayısı olduğu gözlenmiştir./ It was observed that the most effective machine learning method was the decision tree algorithm and the 3 most effective parameters affecting the FEC value were fiber attenuation, number of links and number of channels

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Machine Learning Algorithm Estimation and Comparison of Live Network Values of the Inputs Which Have the Most Effect on the FEC Parameter in DWDM Systems

Araştırma Makalesi / Research Article

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ABSTRACT

The purpose of this study is to determine the effect of 7 different algorithms on the FEC value, which is one of the most important parameters of the quality measurement metric in DWDM networks, analyzing these changes through machine learning algorithms has determined which parameter is the most important input affecting the FEC parameter according to the live network values. To determine the algorithm that gives the most accurate FEC value according to the estimation results in machine learning, it is aimed to make analyzes vendor agnostic. As a result; In this analysis, which was conducted with 945 live network values from 3 different vendors, it was determined that the most important parameters affecting the FEC value are the number of channels, fiber attenuation, and fiber distance, and these parameters were estimated most accurately with the decision tree machine learning algorithm.

Keywords: DWDM performance, performance measurement, FEC, machine learning.

DWDM Sistemlerinde FEC Parametresine En Çok Etki Eden Girdilerin Canlı Ağ Değerlerinin Makine Öğrenimi Algoritması Tahmini ve Karşılaştırılması

ÖZ

Bu çalışmada, telekomünikasyon alanında kullanılan DWDM sistemlerinde kalite metriklerinde en önemli parametrelerden biri olan FEC değerinin, DWDM sistemlerinde toplam 7 farklı metriğe karşı değişimi gözlemlenmiştir. Bu değişiklikler makine öğrenmesi algoritmaları ile analiz edilerek, canlı ağ değerlerine göre FEC parametresini etkileyen en önemli girdinin hangi parametre olduğu belirlenmiştir. Makine öğrenmesinde tahmin sonuçlarına göre en doğru FEC değerini veren algoritmayı belirlemek için vendordan bağımsız analizler yapılması hedeflenmiştir. Sonuç olarak; 3 farklı vendordan 945 canlı ağ değeri ile gerçekleştirilen bu analizde FEC değerini etkileyen en önemli parametrelerin kanal sayısı, fiber zayıflaması, fiber mesafesi olduğu belirlenmiş ve bu parametrenin en doğru şekilde tahmin edilmesi karar ağacı makine öğrenme algoritması ile sağlanmıştır.

Anahtar Kelimeler: DWDM performansı, performans ölçümü, FEC, makine öğrenmesi.

1. INTRODUCTION

We live in a world where ease of access and fast access to information is critical and this need is met with Wavelength Division Multiplexing (WDM) networks. WDM networks are used for data transmission over long distances at high capacity. It is known that the performance of WDM networks should be measured continuously.

Manual analysis of end-to-end performance metrics in large networks, independent of the manufacturer causes a significant loss of labor and time. In addition, in these manual analysis outputs; The success rate may vary according to the experience of the operator. Automatic correlation of the relevant parameters affecting the performance metrics and determining the impact status will eliminate the disadvantages of manual work.

Determining the most important metrics that can be taken as inputs affecting customer service performance and revealing the effect levels of these metrics on the forward error correction (FEC) parameter is an important indicator for ISPs to provide high QoS metrics to their customers.

Dense wavelength division multiplexing (DWDM) network performance measurement results are available in the literature. In some studies, special simulation programs were used for performance measurement [1-2], optimizations were made with genetic algorithms [3-6], different network optimizations were studied [7-14], and

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machine learning algorithms were used [15-17]. In the literature, it is stated that the effect of FEC and Bit Error Rate (BER) metrics [18] on quality values is quite important. These metrics are

- Optical Channel Capacity,
- Total fiber distance traveled by the Optical Channel (km) (Total Link Distance),
- Total Optical Regeneration Number of the Optical Channel (Span Number),
- Optic Regeneration Number (Average Link Span Length),
- A to B Average between two DWDM systems cable attenuation, (dB),
- B to A Average cable attenuation between two DWDM systems, (dB),
- Fiber optic cable expected attenuation value (Total fiber optic cable expected attenuation value),
- Average Fiber Kilometric Loss (dB/km).

In this study; unlike the studies in the literature, machine learning algorithms were created using FEC parameters [19-24], and all the values of the parameters affecting the FEC value were determined to end by automation. Then, using these inputs, it was determined which of the 7 different machine learning values was the most accurate FEC output value by comparing it with the live network measurement values. The most important motivation is the end-to-end analysis of these metrics with vendor-agnostic..

2. METHOD

The data obtained in this study as Regression. Machine learning algorithms can be mentioned as follows;

Random Forest: This algorithm, it is aimed to increase the classification value by generating more than one decision tree during the classification process. A decision forest is created by combining the produced decision trees. Decision trees in the decision forest are randomly selected subsets from the dataset they are connected to [25].

Decision Tree: In this classification method, decision nodes and leaf nodes are created according to the feature and target. Classification is done by creating a tree structure from these nodes. This algorithm has been developed by dividing the dataset used into very small pieces. A decision tree can contain both categorical and numerical data [26].

Boosted Trees Regression: In this algorithm, different types of variables are handled and missing data is detected. There is no need to transform data or eliminate outliers before starting work. They can fit highly complex nonlinear relationships and automatically process the interaction between estimators. The multiple tree placement approach eliminates the disadvantages of single tree models. Although these algorithm models are complex, they can be summarized in ways that provide strong ecological insight. In addition, their prediction performance is superior to most traditional modeling methods [27].

Linear Regression: Regression analysis is the most common method used to model the relationship between two or more variables. If a single variable is used as an input in the model used to estimate the dependent variable, it is called single regression, and if more than one variable is used, it is called multiple regression analysis. The relationship between the dependent and independent variable or variables can be linear or curvilinear. With regression analysis, information can be obtained about the existence of the relationship between dependent and independent variables, and if there is a relationship, its strength. In Multiple Linear Regression, there is a linear relationship between n independent variables (X1, …Xn) and dependent variable (Z) [28].

Ridge Regression: When there is multicollinearity, the Ridge Estimation Method, one of the biased estimation methods, allows all necessary variables to be included in the model. This method aims to obtain parameter cross-sections with smaller variances than LCC estimations when there is multicollinearity and to remove unnecessary variables from the model [29].

Lasso: Least Absolute Contraction and Selection Operator Regression (shortly called Lasso Regression) is a modified version of Linear Regression. It adds an order term to the cost function, but uses the L1 norm instead of half the square of the L2 norm of the weight vector, just like in Ridge Regression [30].

Elastic Net Regression: It is a linear regression model in which the coefficients are trained with both L1 and L2 norm regularization. Elastic Net is a middle ground between Ridge Regression and Lasso Regression. The regularization term is a simple mixture of both Ridge's and Lasso's regularization terms, and the mixing ratio can be controlled by the coefficient r. When $r = 0$, Elastic Net is equivalent to Ridge Regression, and when $r = 1$, it is equivalent to Lasso Regression [31].

Forward Error Correction (FEC) values, one of the most important quality parameters of optical channels carried on dense WDM (DWDM) network, were taken as the data set. If the FEC value, which indicates that there are deteriorations during the transportation of the service, is high, the parameter causing these deteriorations was examined by machine learning.

FEC is a technique used for fiber optic systems. Signal disturbance effects occurring in fiber optic cable are Hamming code, Reed-Solomon code, Bose-Chaudhuri-Hocquenghem code, etc. can be corrected using algorithms [32-33]. In DWDM systems, faults on channel cards with optical channel resources can be healed using a number of FEC algorithms, including carriers that can be corrected by FEC algorithms. In this way, the problems that occur during data transmission are eliminated and the services carried to the subscribers are not interrupted. However, uncorrectable errors are called

FEC errors and also indicate some problems with DWDM optical channels. In this study, analyzes were made on the metrics that may cause the FEC value to be high in DWDM Optical Channels.

In this study, the effect of 9 different parameters on the FEC value was analyzed by using 7 different machine learning algorithms. The most important parameter for the FEC value in each algorithm is determined. Similarly, the success rates of each algorithm were extracted and the most important parameter affecting the FEC value and the most accurate algorithm was determined. In data sets, FEC value, result (Target), and other inputs are defined as inputs. In each study, the RMSE (Root Mean Square Error) gives the success status of the relevant algorithm. Data set values were created for 945 links over the Live Network. These values are applied to the system with the abbreviations in the table below.

Table 1. Inputs of the machine learning

Abbreviation	Explanation
A	Optical Channel Capacity
B	Total fiber distance traveled by Optical Channel (km) (Total link Distance)
C	Total optical regeneration number of the Optic Canal (Span Number)
D	Optic Regeneration Number (Average Link Span Length)
E	A to B Average cable attenuation between two DWDM systems, (dB)
F	B to A Average cable attenuation between two DWDM systems, (dB)
G	Fiber optic cable expected attenuation value (Total fiber optic cable expected attenuation value)
H	Average Fiber Kilometric Loss (dB/km)
I	Number of channels in DWDM links.

3. EXPERIMENTAL SETUP

In this study, the data used in machine learning are taken from a live network where active traffic is flowing through fiber optic cables at various distances. Using real measurement values from a live network ensures that the outputs are more reliable values. The parameters specified in Table 1 were taken on the network, and the measurements were obtained from different points. The most important feature of the network is that there are multiple connections between large and different DWDM systems. Similarly, there are different channel numbers and different channel rates carried from each link. An example connection diagram between the two systems of the examined network is shown in Figure 1. The whole network is connected in the form of a network with similar connections.

In Figure 2, the Turkey-wide DWDM map and links can be seen. In this study, DWDM network data in Figure 2 was used.

Figure 2. DWDM Network Map

The data set which created by taking the data from different vendors over the network as shown in the diagram below. Figure 3 shows this structure schematically. In this schematic structure, the data received from different vendors throughout Turkey are collected on a single system and an environment is created where this data can be analyzed. These data are created with the data received from the network management systems of different vendors. Data was collected with a different algorithm for each vendor. The data is gathered in XML format, from CLI and through CSV export from 1st, 2nd and 3rd vendors respectively.

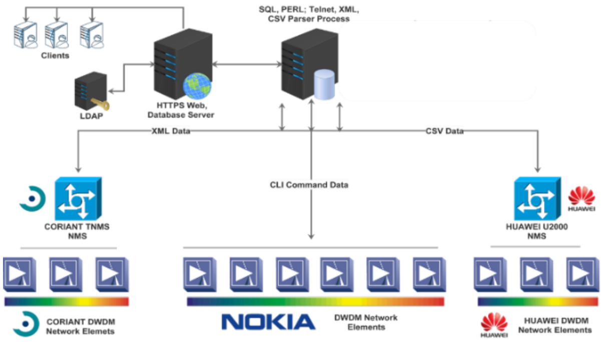

Figure 3. Schematic Structure of Dataset Map

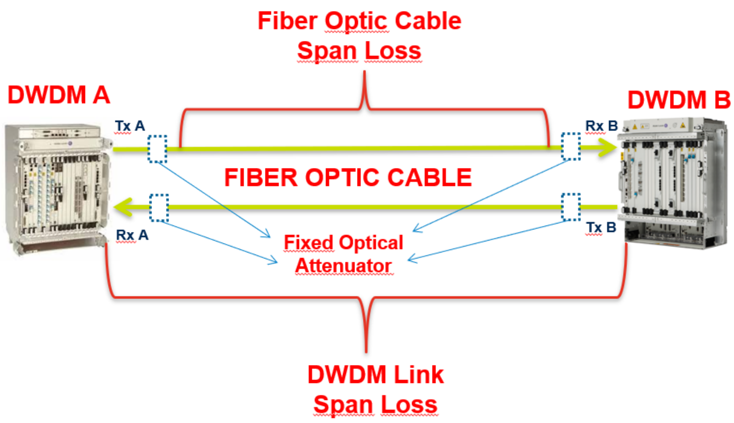

Figure 1. Sample Connection Diagram

Table 2. Sample data set

FEC	OCH Name	Number of span	Link distance (km)	A TO B Attenuation (dB)	B TO A Attenuation (dB)	Fiber Expected attenuation (dB/km)	Fiber kilometric attenuation (dB/km)	Number of channels
188784226426	Ulus_10634-G.antep(SahinBey)_12703-OCh-265314	18	61	20	18	275	0,33	77
188784226426	Hatay_13106-Kilis_17901-OCh-03478	16	57	279	278	229	4,88	58
188654204621	Bozyazi_13301-Mersin_B.Evler_13307-OCh-03967	12	76	281	264	228	3,70	56
172532533595	Mersin_13305)-Adana_10111-OCh-05940	2	45	4	7	22	0,09	64
171536459762	Kars_13601-Erzurum_Sanayi1_1250-OCh-01627	12	63	218	221	190	3,43	58
144418603283	Hatay_13106-Kilis_17901-OCh-03478	16	57	279	277	229	4,88	58
127528229242	Bozyazi_13301-Mersin_B.Evler_13307-OCh-03967	12	76	281	264	228	3,69	56
97595563677	Kars_13601-Erzurum_Sanayi1_1250-OCh-01627	12	63	217	221	190	3,42	58
50612931046	Ulus_10630_100G-Kapitan_Sari_18608-OCh-04108	208	53	2510	2514	2768	47,15	17
39275210198	EDIRNE_12221-Kaptian_Mavi_18604-OCh-272087	20	21	168	162	106	7,89	78
36924381446	Kayseri_13805-Incesu_10615-OCh-05953	15	79	263	276	297	3,33	32
36924381446	Kayseri_13805-Incesu_10615-OCh-05953	15	79	263	276	297	3,33	32
34963551392	ULUS_KUCUKSANAYI_ASON_Ch51_TRANSIT_061651	110	60	1936	1847	1659	32,09	35
34187564397	Samsun_15504-Samsun-Siteler_15501-OCh-02297	4	3	12	16	3	4,49	62
26738451471	ERZURUM_DILUCU_ASON_Ch39_TRANSIT_257639	27	55	446	459	374	8,05	22
25879823376	13701/Kastamonu-15701/Sinop-OCh-00052	6	126	191	212	189	1,51	58
25263220860	Mersin_13304-Karaman_17001-OCh-04086	20	62	423	428	312	6,77	58
24224734059	Adana_10101-S.Urfa_16301-OCh-02026	21	69	300	300	360	4,38	59
23158293330	KUCUKSANAYI_EDIRNE_ASON_Ch69_TRANSIT_162269	90	71	1658	1623	1590	23,46	52
21308322408	Batman_17204-Siirt_15601-OCh-02210	9	35	122	114	79	3,48	56
20206811202	Incesu_10629_100G-LOZENEC_18629-OCh-05924	84	70	766	732	1480	10,86	14
16967598912	EDIRNE_12214_100G-LOZENEC_18629-OCh-230001	27	72	539	539	487	7,47	64
13606751408	ERZURUM_TURKGOZU1_ASON_Ch73_TRANSIT_257573	36	63	721	670	566	11,48	44
13388589664	Adiyaman_10206-Kayseri_13806-OCh-03725	32	68	608	621	548	8,87	60

Data received from different vendor network management systems across Turkey are kept on a server. Since these data are taken over the live network and their performance is followed directly on live data without using any simulation program, it offers the opportunity to observe the metric-based data set with almost 100% accuracy. In this data set, the following metrics, which are not included in the management systems and that we think affect the quality parameter, are taken from different systems and added manually;

- Total link distance,
- Amplifier type
- Attenuation per kilometer (dB)
- Link fiber length (km)
- Expected attenuation data (dB)

With this added data, service-based end-to-end performance monitoring can be performed, even if there are different vendor transitions. For the service started through the A vendor, even if the backbone transitions across Turkey are via the B vendor or the C vendor, end-to-end quality metrics can be followed and problem areas can be depicted. Examples from the data set obtained from the structure in Figure 3 across Turkey are given in Table 2.

4. RESULTS

In this study, for all machine learning algorithms, each input value was handled individually and analyzed according to the FEC value and estimation was made with continuous values. 20% of the data set was used as validation data. The analysis structure obtained for all algorithms is shown in Table 3.

When Table 3 is examined, the fastest trained algorithms are Rigde regression and decision tree algorithms. Parameters with a high impact on FEC output for 945 inputs are given in Table 4. As seen in Table 4, the most important inputs affecting the FEC value are;

- Number of channels in DWDM links (I.)
- Fiber Attenuation, A to B Average cable attenuation between two DWDM systems (E.)
- Total fiber distance traveled by Optical Channel (km) (Total link Distance) (B)

It has been observed that these values match exactly when compared with the live network

Table 3. The analysis structure for all algorithms

Algorithms	Maximum Number of Iterations	Number of trees	Max tree depth	Training time (sec)	Solver
Random forest	10	10	6	0.0610	
Decision tree	-	-	6	0.0094	
Boosted trees regression	-	10	6	0.0704	
Linear regression	-	-	-	0.0029	Newton
Ridge regression	-	-	-	0.0033	Newton
Elastic net regression	-	-	-	0.0599	Fista
Lasso	-	-	-	0.0605	Fista

Table 4. Inputs affecting FEC parameter

Highest Positive Coefficients	
I	553132987.4
E	331980311.7
B	192903430.5
H	72898119.1
D	5174384.755

In Figure 4, the error results obtained from all algorithms are given. As a result, it can be clearly seen that the Decision Tree algorithm made the most accurate FEC estimation with the relevant input parameters. The accuracy of the machine learning algorithms used was examined and it was observed that the decision tree algorithm had the highest success rate with 93%, while the success rates of other machine learning algorithms were; Boosted tree regression at 88%, random forest at 72%, and ridge regression 51% accuracy.

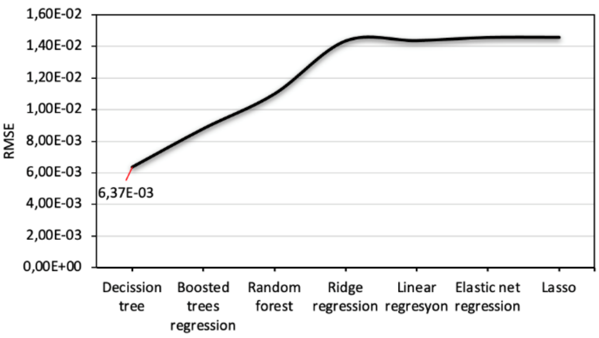

Figure 4. Error Graph

5. CONCLUSION

In this study, the parameter sets taken over the live network were transferred to the database system to be processed on a single platform. This data, obtained from the backbone links throughout Turkey, was taken from different vendors and tried to be processed and analyzed end-to-end. As a result of this analysis, end-to-end links were optimized by looking at the FEC parameter, which is the most important quality parameter valid all over the world. Although these optimization stages are manual, the links have to be examined one by one, and it is difficult to know which parameter has the highest effect on the FEC value, the most accurate estimation was made with the 7 machine learning algorithms used in this study, and the FEC parameter was sampled as closest to the live network value and the FEC parameter was the lowest. This study shows the top 3 parameters affecting the FEC: the number of channels, fiber attenuation, and fiber distance. Automated which parameters are most effective to improve the FEC value at the optimization point. With this analysis, ease of use is provided for operators in systems that manage large networks and have different vendors in these large networks. In addition, instead of manually following the FEC parameter, the indicators in the network are used as inputs in the Decision tree algorithm and thus the estimation of the Quality values for the new links to be opened is made possible.

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

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