Research Report
KTC-04-28/SPR-264-02-1F

KENTUCKY TRANSPORTATION CENTER

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STATE TRAFFIC VOLUME SYSTEMS COUNT ESTIMATION PROCESS

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State Traffic Volume Systems Count Estimation Process

by

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16. Abstract

The Kentucky Transportation Cabinet has an immense traffic data collection program that is an essential source for many other programs. The Division of Planning processes traffic volume counts annually. These counts are maintained in the Counts Database (CTS), which contains over 20,000 separate station locations and some traffic counts from as early as 1963.

The Division of Planning currently collects traffic volume counts for all non-interstate routes on a revolving three-year basis. Years wherein actual counts are not performed are supplemented with estimates generated by a FORTRAN program. Estimates are projected using prior actual counts by weighted linear regression methods. If an actual count is performed during the fiscal year, this count then replaces the estimated count. These traffic volume counts, both actual and estimated, are compiled into the Traffic Volume System (TVS).

The focus of this project was to research potential estimating methods to fulfill the above mentioned requests and to analyze possible contributing factors to traffic volume counts such as traffic growth, population, and economic development.

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The Division of Planning currently collects traffic volume counts for all non-interstate routes on a revolving three-year basis. Years wherein actual counts are not performed are supplemented with estimates generated by a FORTRAN program. Estimates are projected using prior actual counts by weighted linear regression methods. If an actual count is performed during the fiscal year, this count then replaces the estimated count. These traffic volume counts, both actual and estimated, are compiled into the Traffic Volume System (TVS).

This database is the source file for various reports produced by the Kentucky Transportation Cabinet. Annual Average Daily Traffic (AADT) is vital to many efforts including the Highway Information Systems and the Highway Performance Monitoring System (HPMS). AADT is reported annually to the Federal Highway Administration. With these significant contributions of the TVS, the Division of Planning has deemed necessary an evaluation of the current process for estimating traffic volume counts. Specific revisions requested were:

1. Retain a copy of historical estimates that have been replaced with actual counts.
2. Remove TVS from the mainframe.
3. Examine forecasting mechanism for possible revision to minimize erroneous outliers in estimation process.
4. Potential inclusion of growth factors into estimation process.

The focus of this project was to research potential estimating methods to fulfill the above mentioned requests and to analyze possible contributing factors to traffic volume counts such as traffic growth, population, and economic development.

As with any system, the quality of the data will determine the accuracy of the results. Although there has been much attention focused on the quality control of traffic counts, error is inherent to this process with so many variables in the traffic patterns and flow. Automated Traffic Recorders (ATR), which record traffic data continuously 365 days a year would be the ideal solution. These recorders would capture an accurate model of daily traffic that can only otherwise be mathematically manipulated at best. Kentucky currently has 99 ATR's, and has plans to implement additional ATR's in the future. However, with the expense of the recorders and the required maintenance involved, the implementation could be a slow process.

An advantage of neural networks is their ability to allow the data to become the model, rather than imposing a presumed relational equation upon the data. With each county having its own neural network, traffic volume estimates can more accurately reflect the traffic volumes in each county. Although the population and employment data is county-based, the addition of these growth factors will enhance the networks ability to adjust to fluctuations that might not have been detected otherwise. With this new estimating process, the advance in transportation technologies and the continuing efforts of the Division of Planning, Kentucky should remain a forerunner in transportation.

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1.0 Introduction

The Kentucky Transportation Cabinet's Division of Planning recognized that the current process for estimating traffic volumes should be evaluated and if possible, improved upon. The current system, which predicts traffic volumes using a variety of mathematical methods depending on the availability of actual data, has proven to not be sufficient for the current needs of the Division of Planning.

Traffic volume is vital to many efforts of KTC. The Annual Average Daily Traffic (AADT), which is derived from both actual and estimated traffic counts, provides crucial information for the planning of new road construction, travel model design, congestion management, pavement design, air quality compliance, etc. AADT is also used to estimate state wide Vehicle Miles Traveled (VMT), which aids in compliance with the 1990 Clean Air Act Amendment.

In the initial stages of this project, a search was conducted to evaluate the success of other state's traffic count estimation systems. A large part of this data was obtained from a recent report "Analysis of Traffic Growth Rates", published by the Kentucky Transportation Center (*1*). From a survey response of 29 states, it was determined that 81% of states calculated ADT by counting traffic some years and estimating others. For these years of traffic count estimations, 43% of the states used other local road counts in the estimation process.

Many states have customized programs to estimate traffic counts while some use mainstream software. There are various prediction or estimation softwares available; however some form of customization is usually required. Some states use a software package to streamline all traffic information. For example, Wisconsin, Nevada, Delaware, Washington, and Missouri use TRADAS, which is a traffic data collection, quality control, and analysis software package that can also be customized. (*2*)

A literature search on estimating traffic counts proved to be limited. Most information is based on urban areas. One study focusing on county roads was performed by Purdue University. A multiple regression method using aggregated data at the county level was used to predict AADT in 40 counties in Indiana. Four predictors were chosen: county population, access to other roads, location type (rural/urban), and total arterial mileage in a county. Several other studies have also been performed on AADT estimation using predictors such as county population size, location type (rural/urban), personal income level, total number of through lanes, vehicle registrations, etc (*3,4,5, 6)*.

2.0 Review of Current Systems

The first task in the TVS project was to interview the members of the Division of Planning who maintain the current Counts Database (CTS). These employees receive actual counts from various locations across the state each month. These counts are attained through permanent, portable, and index stations. There are approximately 4700 actual counts performed each year. The counts are reviewed for possible errors or flags and then entered into the system, replacing the estimated counts for those particular stations. The standard for data quality is the Count Acceptance Program, CAP, which requires data from portable stations to be +/- 10% error for any given county in a given year. The CTS file is then updated at the end of each month.

The current system for estimating traffic counts is a FORTRAN program that estimates counts based on the number of actual counts in the database. If there are no counts for a particular station, the system uses a statewide average for the corresponding Functional Class. If there is one actual count, the system uses the ratio of data to the Functional Class average by linear growth rate. For two or more actual counts, a piecewise weighted linear fit of actual data points to current year. For estimates prior to first actual count, a ratio of the Functional Class average is computed for a range of one to four actual counts. For five or more actual counts, estimates prior to the first actual are computed by exponential regression.

In an earlier study performed by Kentucky Transportation Center, estimates generated by the FORTRAN program were saved before they were replaced by actual traffic counts and compared as shown in Figure 1.

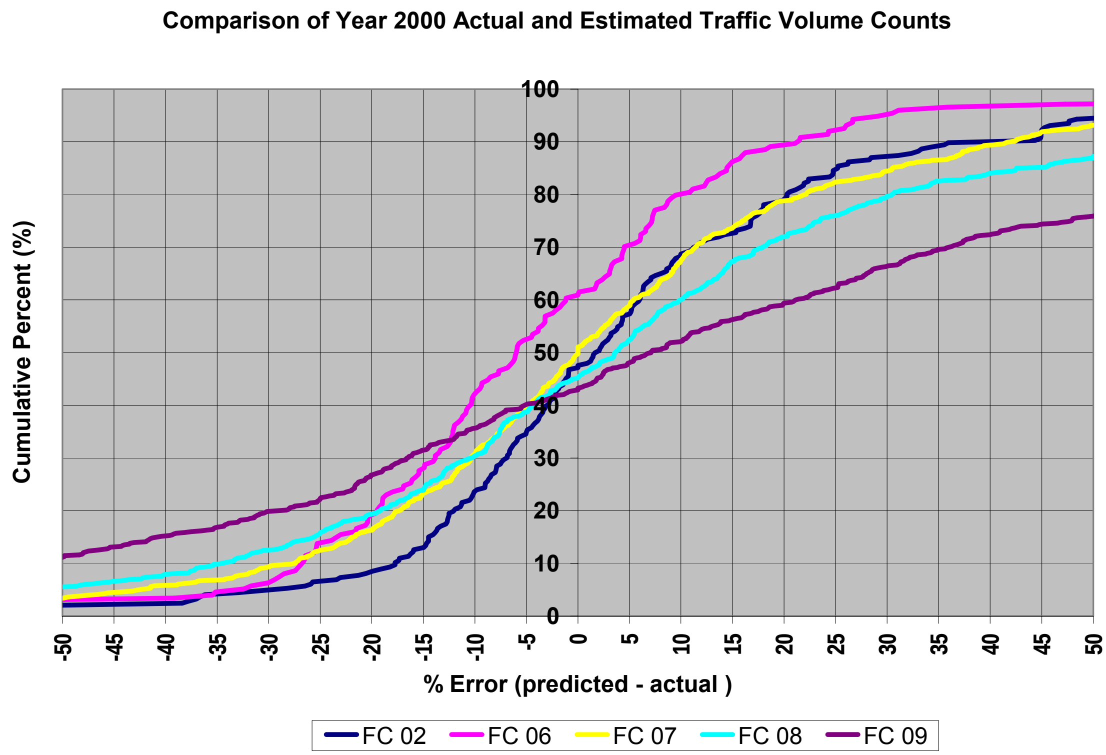


Figure 1. Comparison of Year 2000 Actual versus Estimated Traffic Counts by Functional Class.

Functional Class 02 has the most accurate traffic volume estimates, with 48% of the estimates generated falling within the +/- 10% error guidelines. The least accurate estimates occurred with Functional Class 09, with a sparse 17% of estimates generated resulting in +/-10 % error.

The CTS database itself contains a massive amount of information such as the 18,000 plus stations, their corresponding mile markers and road numbers, functional class, and corresponding traffic data from years 1963 to 2003, with data designated as “A” adjusted by engineer, “E” engineer’s estimate, or “_” computer estimate. Some years contained “0” for counts prior to the implementation of the estimation program. Also included in this database is whether a road has had an “impact year”, or a year in which major changes have occurred such as the construction of a large retail store in close proximity to the road.

After the review of other estimating or prediction software and the CTS database, we recommended the analysis of a neural network to generate traffic volume estimations. Many different neural network software packages were analyzed, however we chose Neurosolutions software for its ease of use and compatibility. The Division of Planning also chose two factors to analyze relationally to traffic volumes: population and economic development or employment per county.

The population information was easily acquired from the Kentucky State Data Center. The employment information on a county basis was limited to years 1975 and forward on computer file. This data was obtained from the Kentucky Cabinet for Workforce Development. With this factor limiting, it was determined that we would only input all data (traffic volume counts, population, and employment) beginning with the year 1975 through 2003.

3.0. Brief Introduction to Neural Networks

Neural networks have been employed in various fields such as finance, engineering, medicine, geology, and physics. The power of neural networks lies within its complex modeling capabilities. Neural networks are nonlinear, thus allowing the problems of prediction, classification, or control to be modeled without the inadequate approximations of linear modeling.

Neural networks are applicable in any situation in which a relationship between independent variables or inputs and dependent variables or outputs exists, even if the correlation between the two is not easily ascertained. If the nature of this relationship was known, it could be modeled easily.

Neural networks are loosely based on the human brain, with multiple layers of processing elements called neurons. Neurons in our brain help us to remember, think, and apply our previous experiences to any circumstance. Neural networks learn by example. A history of data is entered into the network and training algorithms are invoked allowing the network to learn the structure of the data. If the network can learn the structure of the data, it can subsequently be used to predict data where the output is not known.

A simple schematic depicts the most common neural network, a Multilayer Perceptron:

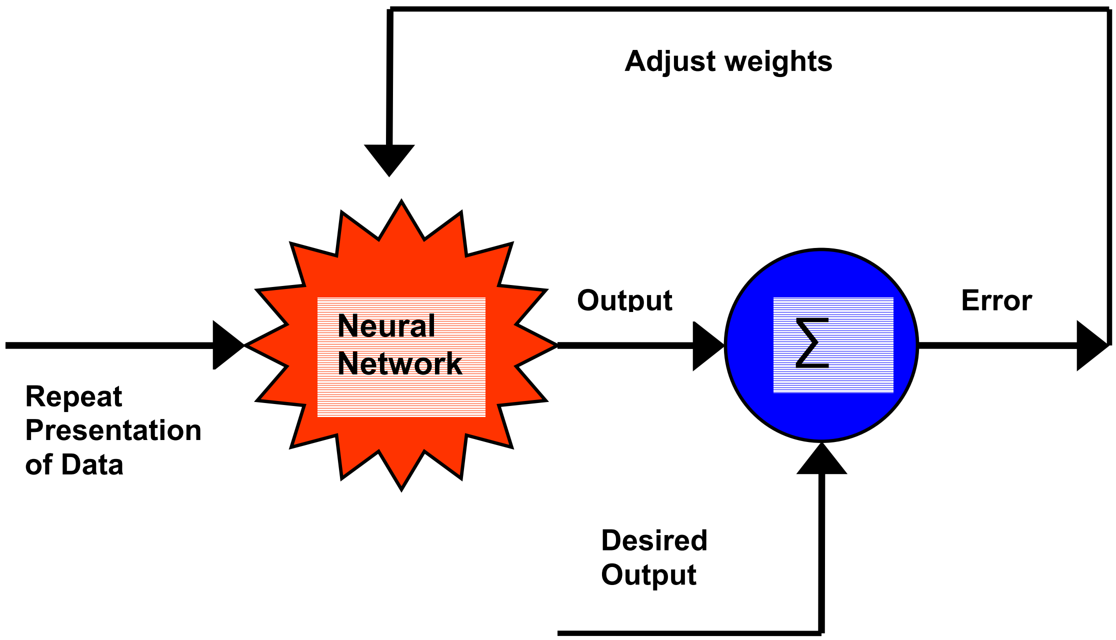


Figure 2. A Multilayer Perceptron diagram.

As shown in Figure 2, the input data is continuously presented to the network and compared to the desired output. After each epoch, or a complete cycle of data presentation to the network, an error is computed and fed back or backpropagated to the network. The network then adjusts the weights so that the error decreases with each iteration, thus allowing the network to closely model the desired output.

4.0 Data Management & Software Capability

Preceding any software simulations, the traffic volume counts had to be extracted from the CTS database. Some of the data required cleaning, as estimated values were tagged with hyphens, adjusted values also contained the letter “A”, etc. Years with zeroes or no count or estimate were replaced with an interpolated value between the two closest year counts.   The population and employment data were downloaded from their respective web sites into Excel™ files.

An advantage to the neural network software is an option for a Microsoft Excel add-in program that allows all tasks to be performed while in Excel™.   This would allow simple data management, such as preprocessing and analyzing data, and more importantly, creating, training, and testing the neural network from within Microsoft Excel™.

There were various techniques analyzed for presenting the data to the network. For the traffic counts, data could be segregated by county or by district. Grouping the data by each district would be beneficial due to the increased amount of data for the network to process or “learn” and would also limit the number of different networks to 12. However, a county-based network would more accurately depict traffic volumes, but would increase the number of networks to 120.

5.0 Final Model Results

A multiplayer perceptron (MLP) was used for each of the 120 counties.   Within each network, 60 % of the data was used for training, 25 % for testing, and 15 % for cross validation. In a few of the counties, all of the data was used for training thus no cross validation was performed (see Table 1 in appendix). The data was presented to the network in the following order: previous year traffic counts, population, employment, and current year traffic counts. The stations were ordered just as they are in the CTS database. The network training was set to load the best weights, use cross validation, and randomize initial weights. Each network’s training was terminated after 1000 epochs.

A separate analysis was performed on some counties by grouping the traffic volume counts by arterials, rural and urban interstates and freeways, and collector and local. Jefferson County, which is one of the largest counties, did not perform well in this analysis. Counties with similar traffic patterns were also grouped together as a trial network. Jefferson, Oldham, Fayette, Jessamine, Clark, Scott, and Madison counties were tested as a separate network. However, the results were not desirable and the trial was discontinued.

The majority of the counties performed well with the simple MLP. Initial performance can be monitored by successful network training. As shown in Figure 3, the cross validation error and training error should approach zero.

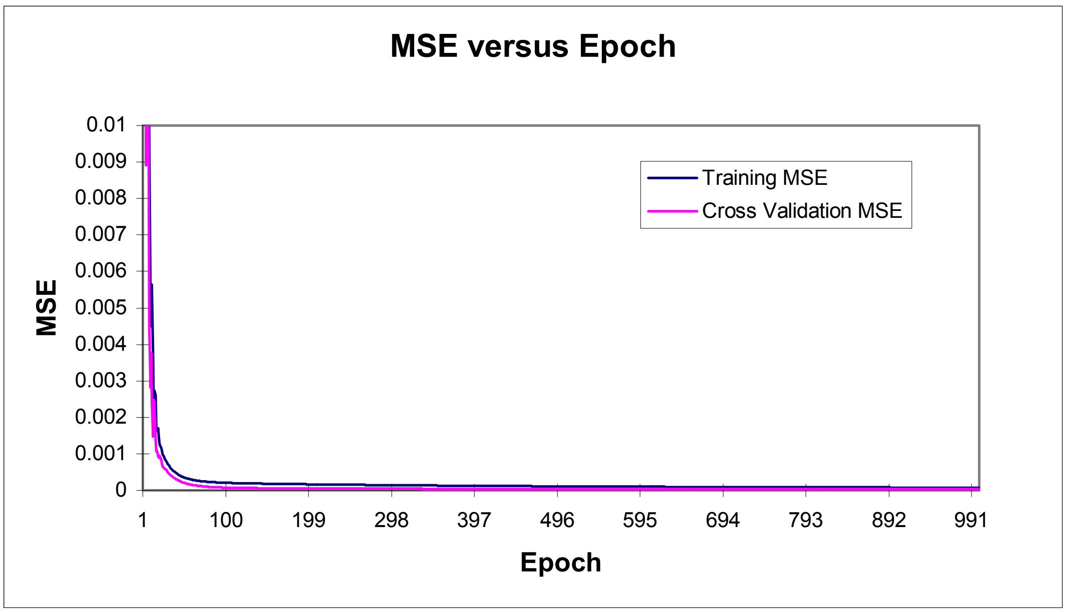


Figure 3. Example of a Successful Network Training.

No more than 3 training sessions were required for any county to achieve a relatively high correlation coefficient (r) during testing. As a general rule, a correlation coefficient of 0.88 means that the fit of the network model to the data is reasonably good. Results from counties randomly selected from each district are shown in Appendix A.

However, 48 of the counties did not perform as well with the initial network. An additional processing element was added to the network and the stations were randomized and then presented to the network. This drastically improved the network performance of these counties which are shown in Table 1.

Table 1. Counties requiring modified MLP networks.

Allen	Harlan	McCreary	Pike
Anderson	Harrison	Magoffin	Powell
Barren	Hart	Marshall	Pulaski
Bell	Hickman	Mason	Rockcastle
Bourbon	Kenton	Mercer	Rowan
Breathitt	Laurel	Montgomery	Scott
Butler	Lawrence	Muhlenberg	Shelby
Caldwell	Leslie	Nelson	Simpson
Casey	Letcher	Nicholas	Todd
Christian	Lincoln	Ohio	Washington
Garrard	Logan	Oldham	Wolfe
Graves	McCracken	Perry	Woodford

An interesting observation can be made when viewing the counties on a state map as shown in Figure 4. Two similar but distinct networks were used in this project. Notice that the counties listed in Table 1 are highlighted in purple in Figure 4. The most common identifiers seem to be the presence of an interstate and/or a major highway system in a non-metropolitan area.

A statistical summary for all counties can be found in the appendix. Training and cross validation results include final mean squared error (MSE) with corresponding epoch number. Testing results include normal mean squared error (NMSE) and correlation coefficient (r). A comparison of the neural network results with the Fortran program results are shown in Figure 5.

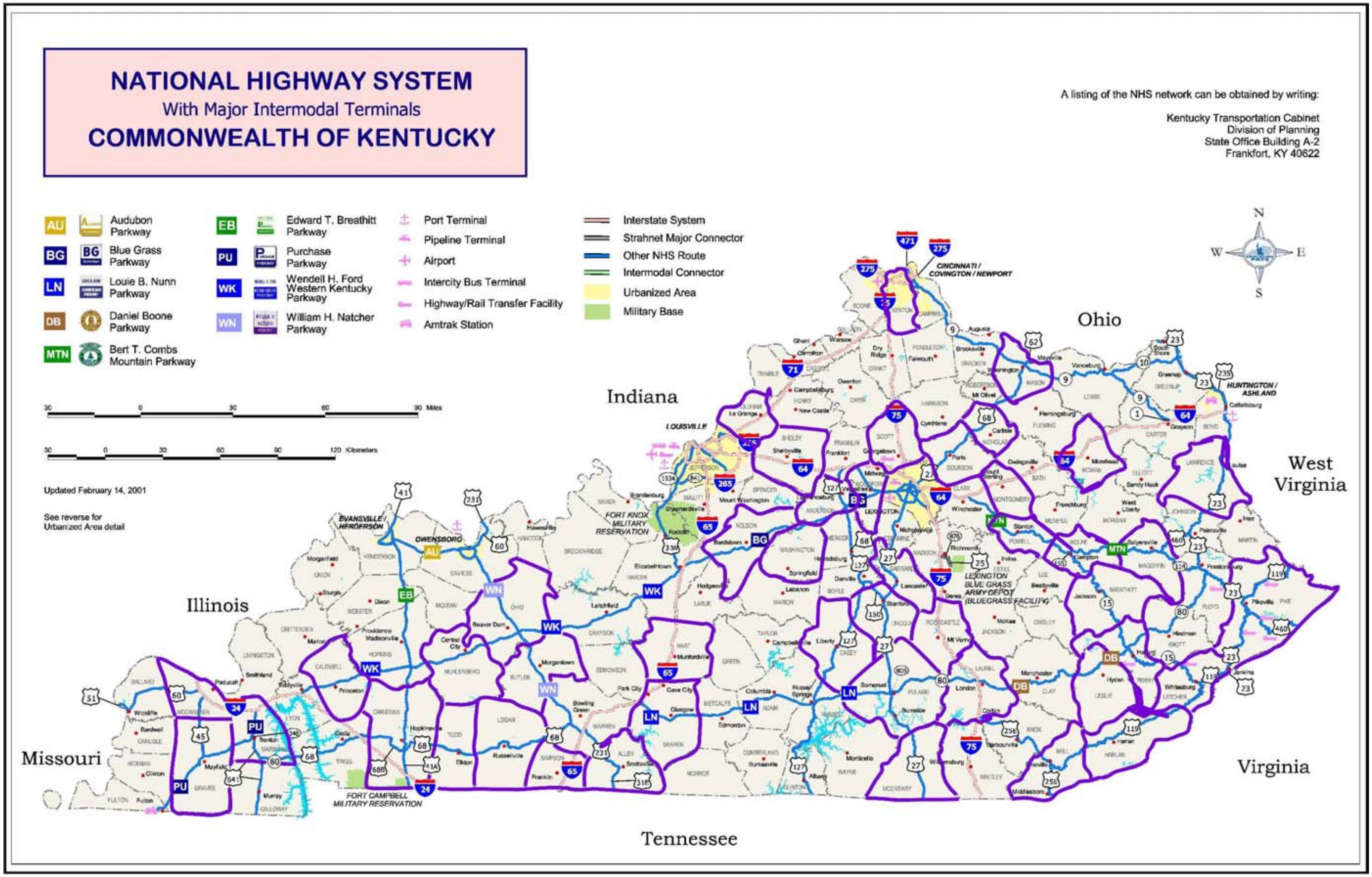
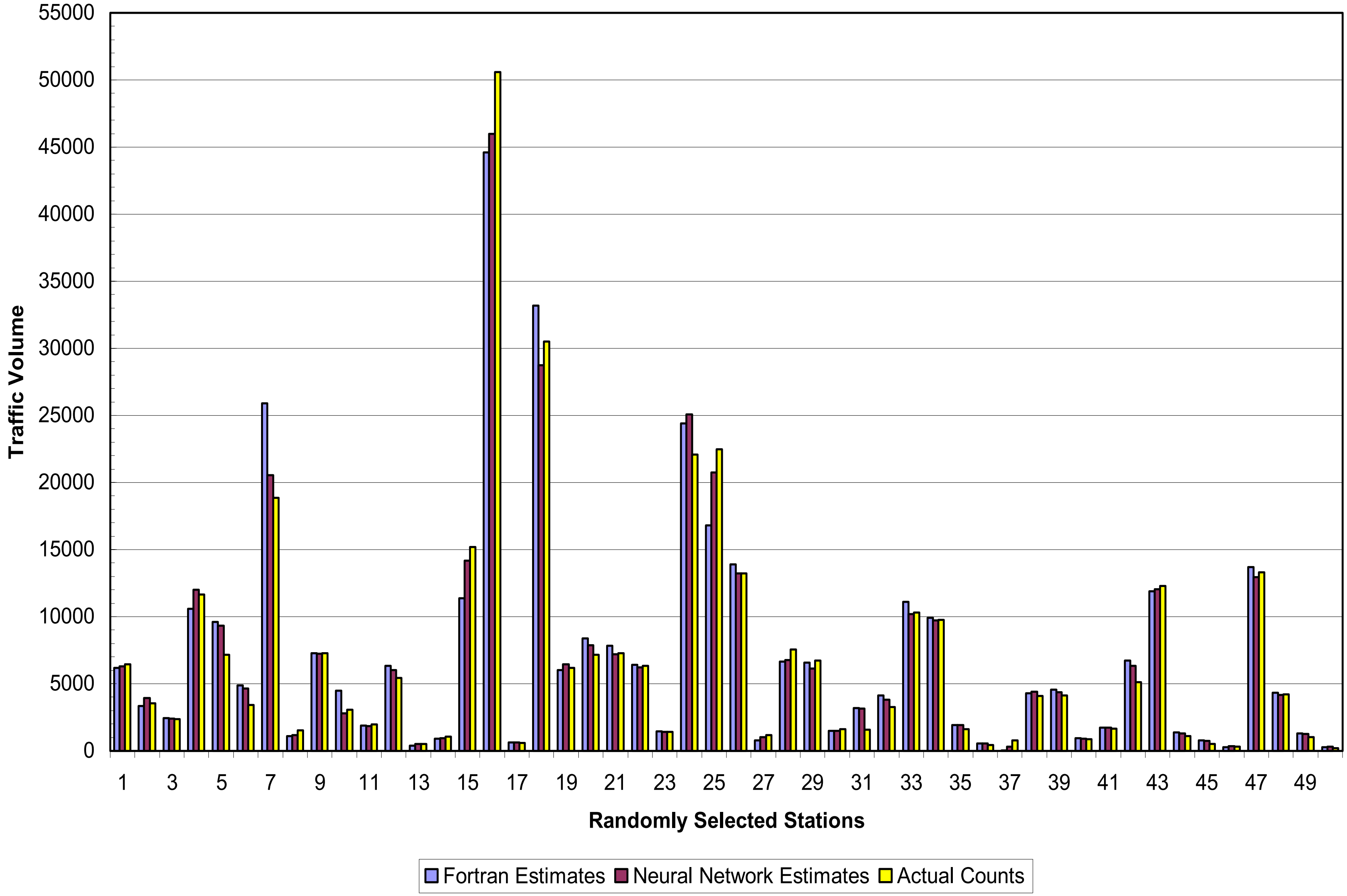


Figure 4. Kentucky Counties with Common Networks.

Figure 5. Analysis of Neural and Fortran Estimates to Actual Counts.



Stations were randomly selected for the analysis shown in Figure 5. Some stations initially selected could not be used due to actual traffic counts for those stations not being taken during 2003. For the 50 stations depicted in Figure 5, the neural network predicted more accurate traffic estimations 76% of the time while the Fortran estimates were closer to the actual counts 24% of the time. The neural network total average percent error was 14.03 % while the Fortran program total average percent error was 18.95 %. See Table 2 for the complete analysis as shown in Figure 5.

These results are quite promising considering the fact that the neural network performed this well while using the current traffic counts database, which contains approximately 66% Fortran estimates at any given time. An interesting evaluation of the network could be performed at the end of the next 3-year count cycle when the database would comprise entirely of estimates from the network itself.

	County	Station ID	2003 Fortran estimate	% Error	2003 Neural network estimate	% Error	Actual
1	1KY	001A57	6190.00	4.31	6302.00	2.58	6469.00
2	2US	2559	3360.00	4.87	3925.11	11.13	3532.00
3	4US	4500	2430.00	3.10	2403.24	1.96	2357.00
4	5KY	005D32	10600.00	9.08	12008.62	3.00	11659.00
5	7KY	007D70	9590.00	33.57	9324.89	29.87	7180.00
6	9KY	009A74	4890.00	42.19	4631.91	34.69	3439.00
7	11US	011A56	25900.00	37.37	20553.89	9.02	18854.00
8	14US	014C11	1090.00	28.10	1166.47	23.06	1516.00
9	16US	016A40	7270.00	0.37	7245.22	0.71	7297.00
10	19KY	019S13	4473.37	45.48	2785.66	9.41	3075.00
11	22KY	022A61	1887.17	5.02	1860.20	6.38	1987.00
12	25KY	025A93	6340.00	16.33	6035.19	10.74	5450.00
13	26KY	26309	378.00	26.17	509.73	0.44	512.00
14	29KY	29005	892.00	15.05	947.40	9.77	1050.00
15	30US	030A54	11393.00	25.05	14175.81	6.74	15200.00
16	34US	034G54	44600.00	11.86	45987.30	9.12	50600.00
17	35KY	035A09	641.00	7.91	618.01	4.04	594.00
18	37US	037A84	33200.00	8.85	28730.57	5.80	30500.00
19	39US	39250	6030.00	2.43	6470.50	4.70	6180.00
20	43TR	43560	8390.00	17.34	7888.49	10.33	7150.00
21	46KY	046A10	7850.00	7.83	7197.64	1.13	7280.00
22	49US	049A30	6400.00	0.95	6212.41	2.01	6340.00
23	52US	52254	1450.00	2.55	1423.85	0.70	1414.00
24	54US	054A33	24400.00	10.41	25075.13	13.46	22100.00
25	56FS	056A74	16800.00	25.33	20736.72	7.84	22500.00
26	59KY	059C76	13900.00	5.22	13209.91	0.00	13210.00
27	61KY	61780	801.00	32.12	1034.59	12.32	1180.00
28	63KY	063A07	6670.00	11.54	6763.73	10.30	7540.00
29	65KY	065A28	6560.00	2.67	6146.41	8.81	6740.00
30	67KY	067A10	1490.00	8.14	1511.67	6.80	1622.00
31	68KY	68018	3190.00	100.63	3145.54	97.83	1590.00
32	72US	072A09	4130.00	25.91	3826.83	16.67	3280.00
33	73US	073B94	11100.00	7.77	10208.60	0.89	10300.00
34	76KY	076C33	9920.00	1.45	9733.81	0.45	9778.00
35	85KY	85513	1910.00	17.18	1923.45	18.00	1630.00
36	86KY	86017	567.00	34.36	546.02	29.39	422.00
37	89KY	89520	57.00	92.69	308.00	60.51	780.00
38	93KY	093B11	4280.00	4.14	4412.59	7.36	4110.00
39	97KY	097A38	4550.00	9.90	4380.38	5.81	4140.00
40	101KY	101014	943.00	7.04	923.84	4.86	881.00
41	102KY	102A18	1720.00	4.24	1728.00	4.73	1650.00
42	105KY	105A90	6730.00	31.19	6345.15	23.69	5130.00
43	106US	106A70	11900.00	3.25	12051.68	2.02	12300.00
44	108KY	108760	1390	24.00	1307.929199	16.68	1121.00
45	111KY	111508	786.00	53.52	752.72	47.01	512.00
46	113KY	113264	283.00	11.56	370.75	15.86	320.00
47	114US	114C23	13700.00	3.01	12935.67	2.74	13300.00
48	116KY	116A70	4350.00	2.84	4190.54	0.93	4230.00
49	118KY	118B38	1310.00	25.96	1243.33	19.55	1040.00
50	119KY	119259	259.00	35.60	324.16	69.72	191.00
			Total % Error	947.44		701.55	
			Avg % Error	18.95		14.03	
		Total Stations Closer to Actual Count		12 (24%)		38 (76%)	

Table 2. Comparison of Neural Network and Fortran Estimates to Actual Traffic Counts.

6.0 Conclusion

The importance of accurately estimating future traffic counts is vital for the Division of Planning. These estimations are the source for many state and federal systems, including Annual Average Daily Traffic (AADT), Highway Information Systems (HIS), and the Highway Performance Monitoring System (HPMS) to name a few. The Division of Planning has established stringent policies such as the Count Acceptance Program (CAP) to assure the quality of these traffic estimations and has also chosen to evaluate the system that produces these estimates.

The current program, which has been in place since 1973, has performed well since its inception but during the latter years has begun to deviate beyond the CAP standard. This may be due to the program's linear estimation method, which does not perform well during years where traffic patterns fluctuate. This weakness of the program led to the analysis with neural networks, which are known for their ability to adapt to fluctuations.

Although the initial performance of some counties with the network was not suitable, modifications to those county networks resulted in more accurate estimations. With closer analysis the similarities of these counties were found to be very high, including the presence of a major highway and/or an interstate in a non-metropolitan area. The ability of the network to adapt to these conditions with a simple change in the network structure proved invaluable. More importantly, this initially poor network performance exposed an underlying trait of these county's traffic volumes that differs from the other counties.

The neural network proved to be a powerful estimating tool that can easily be adapted for specific situations. The requests made by the Division of Planning were to retain historical estimates, remove estimating program from mainframe, minimize outliers in estimation process, and to include growth factors into estimation process. The neural network only tests or produces future year estimates, thus the current and previous years remain intact. The software can also be installed on personal computers. The network also showed promising results, achieving a 76% closer accuracy to actual counts than the Fortran estimates. Lastly, growth factors (employment and population) that largely influence traffic volumes and that were readily accessible were incorporated into the estimation process.

7.0 References

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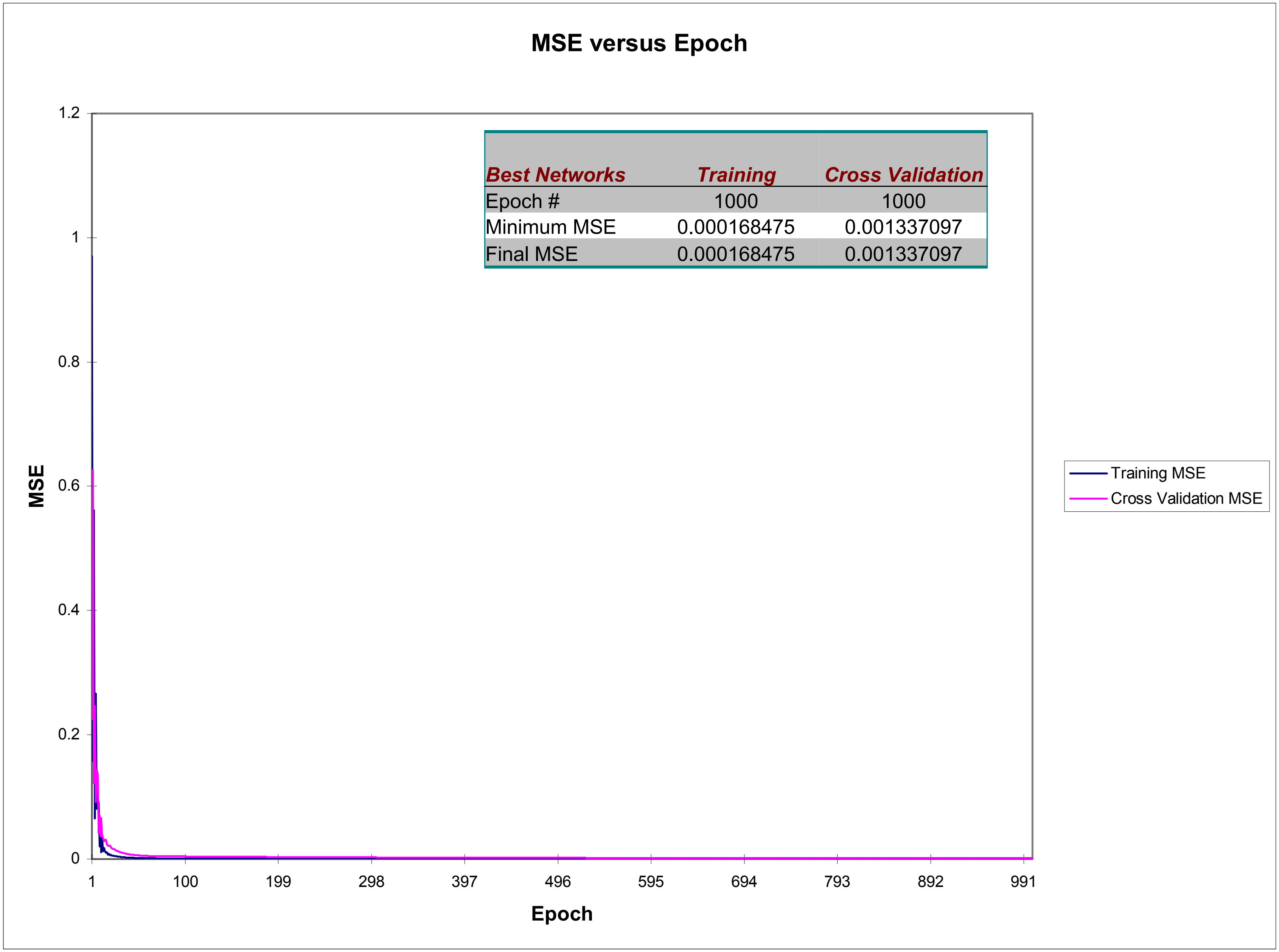
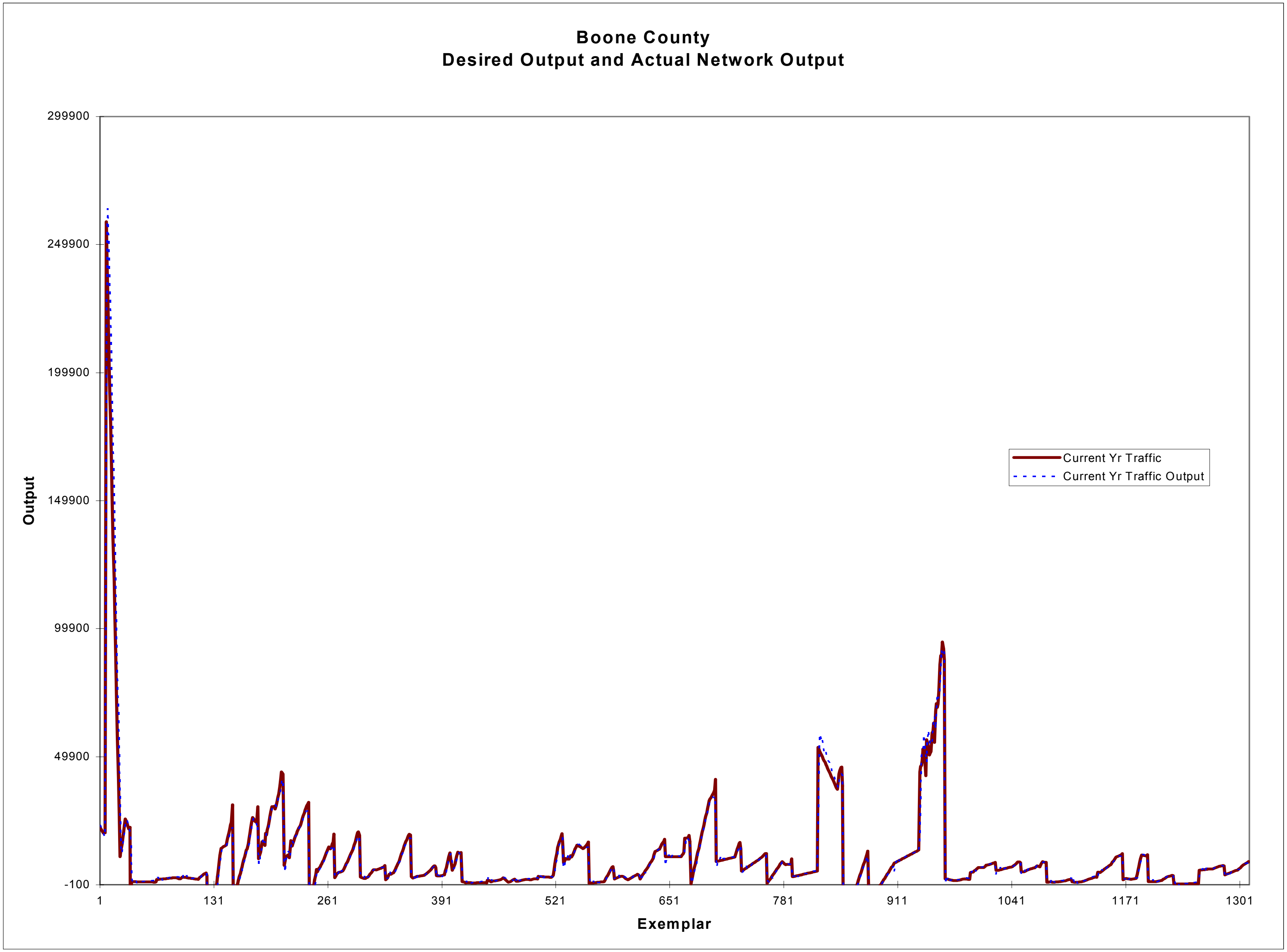
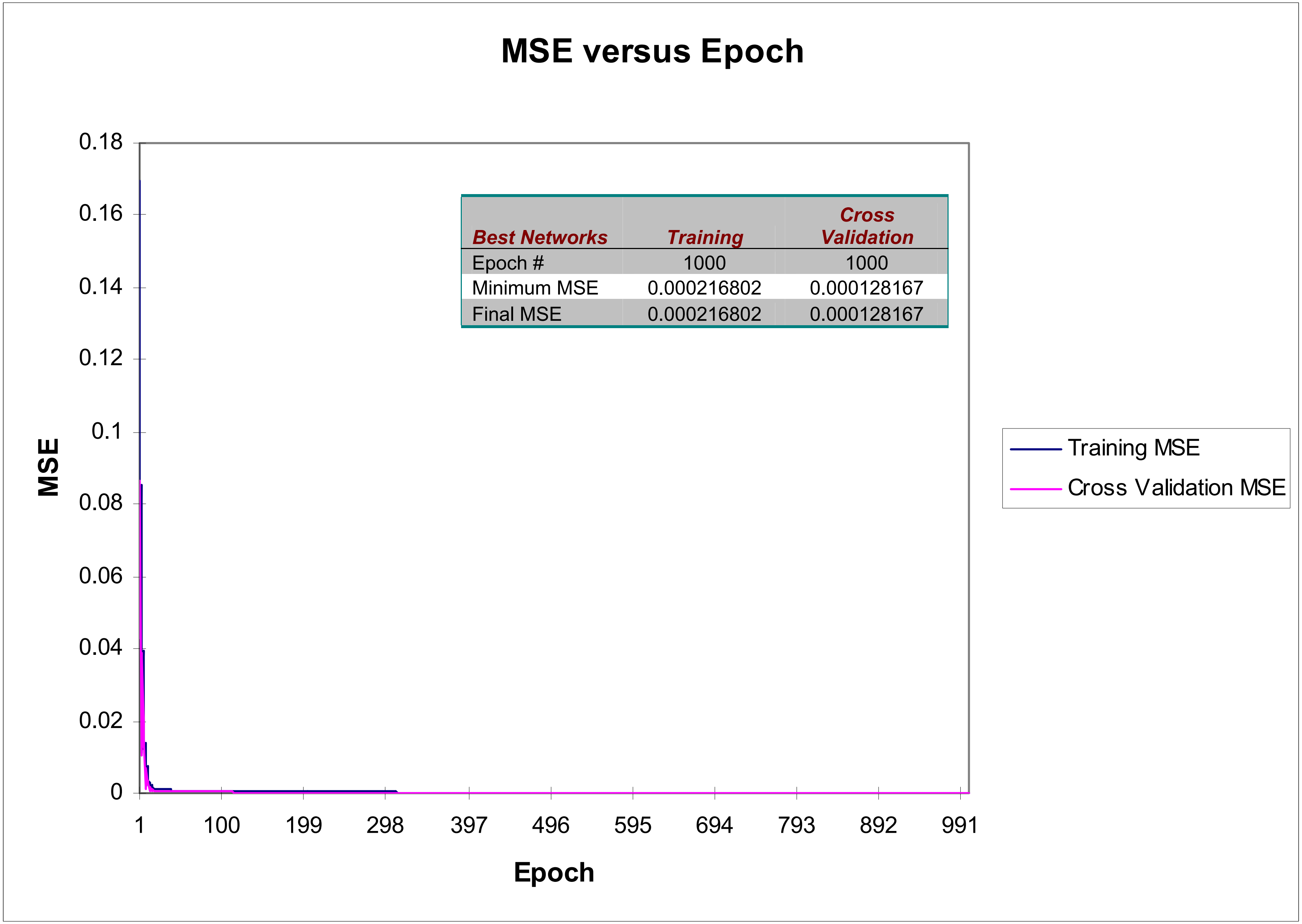
8.0 Appendix



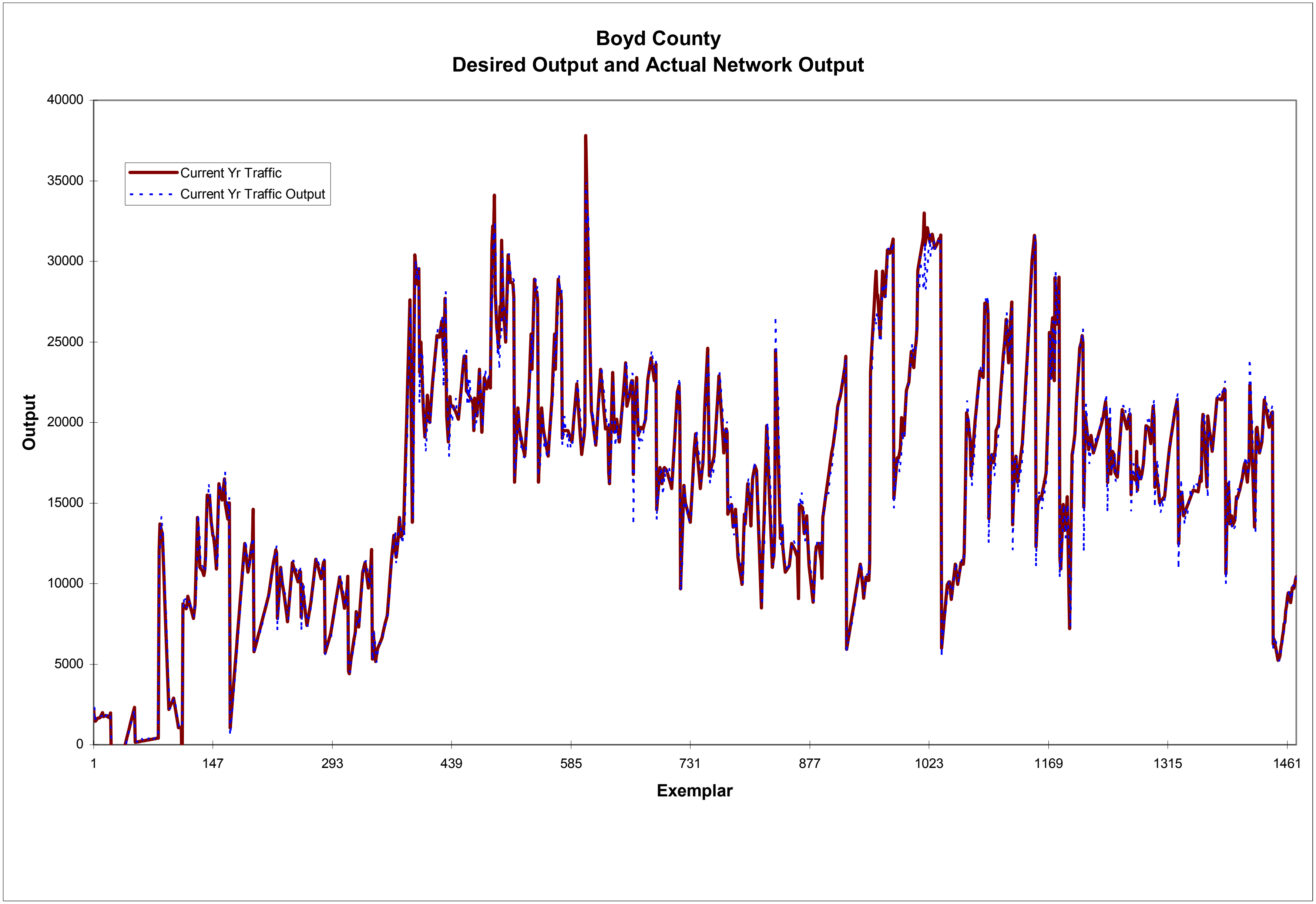
8.1 Boone County Network Training Report.



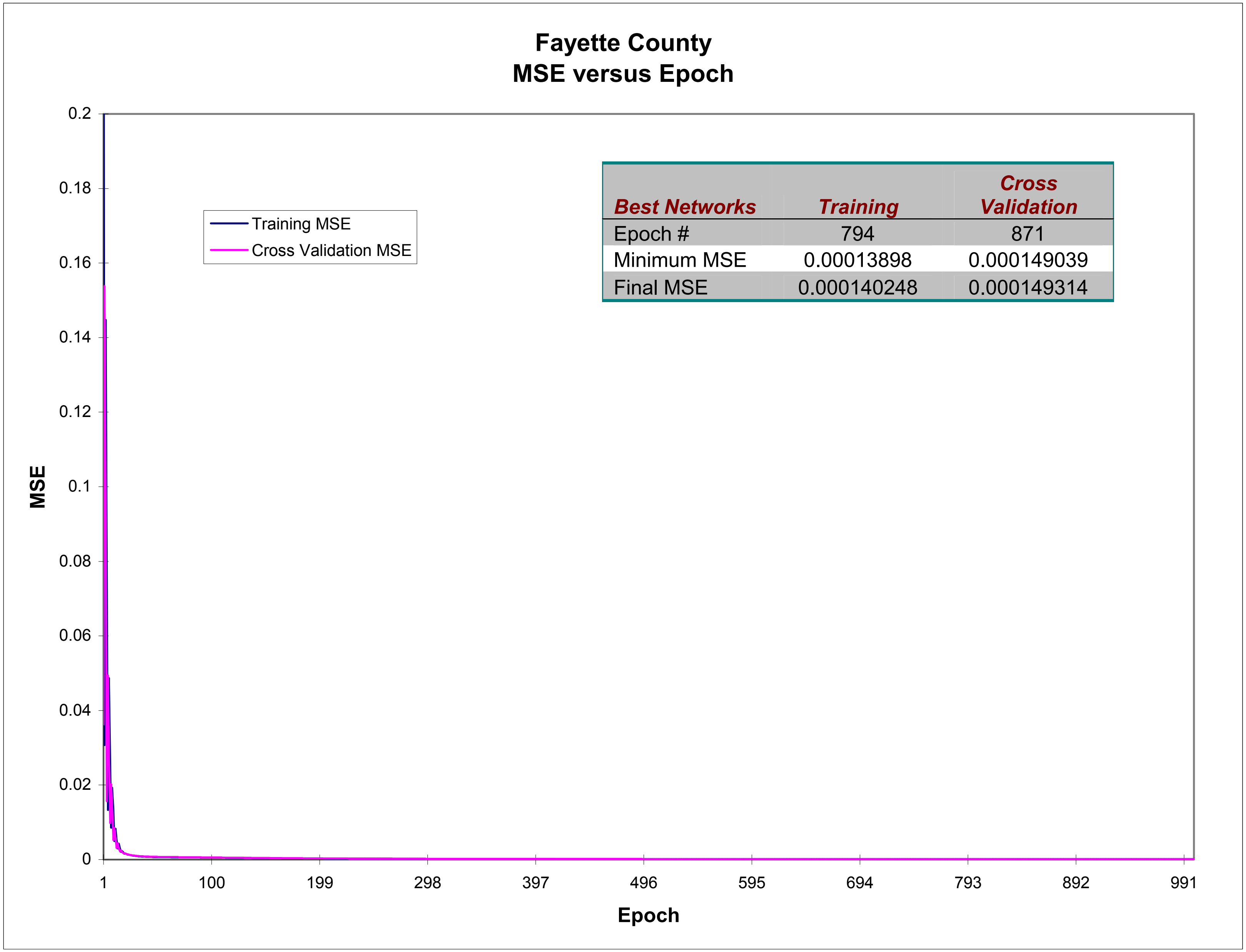
8.2 Boone County Network Testing Report.



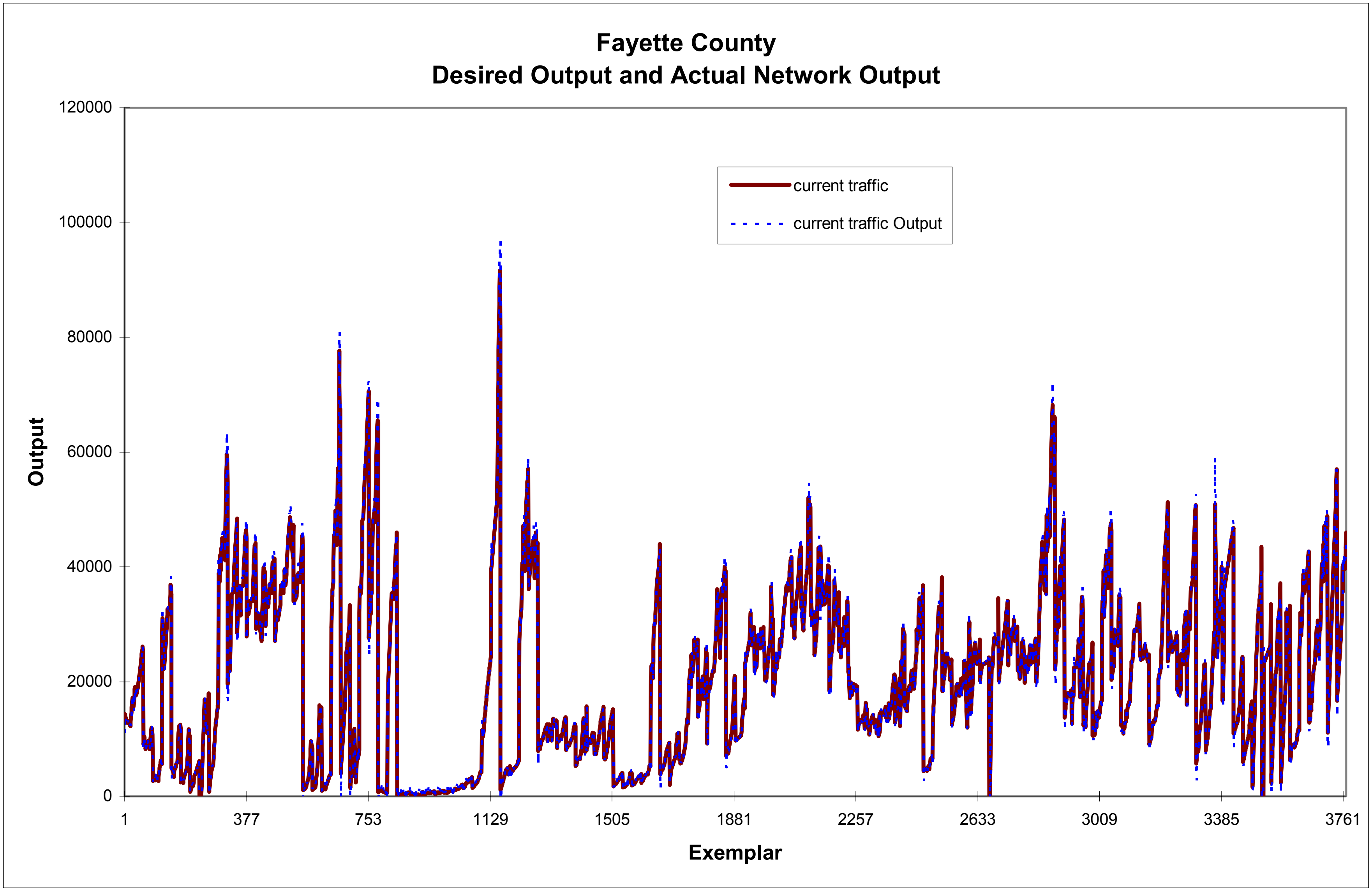
8.3 Boyd County Network Training Report.



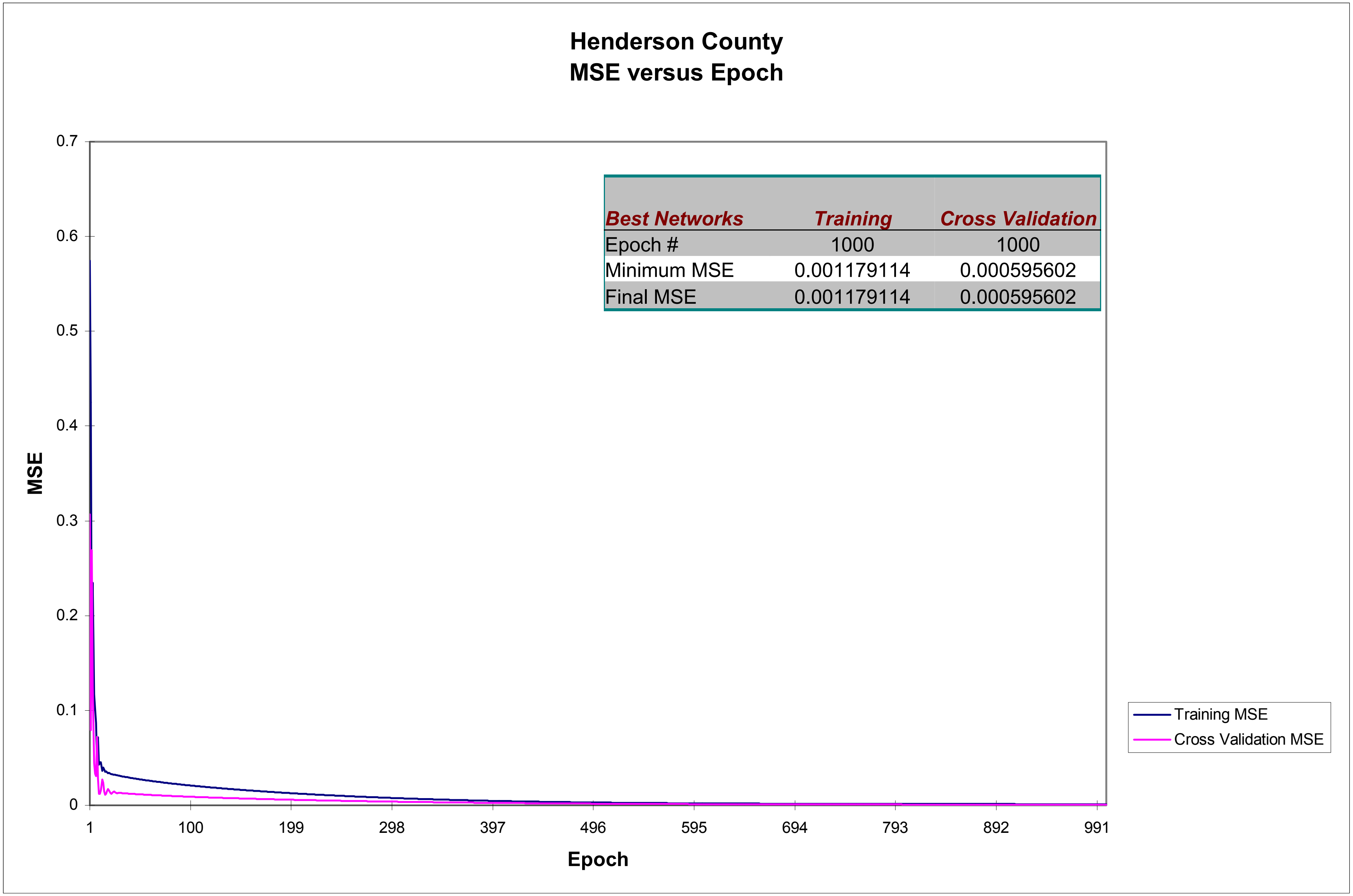
8.4 Boyd County Network Testing Report.



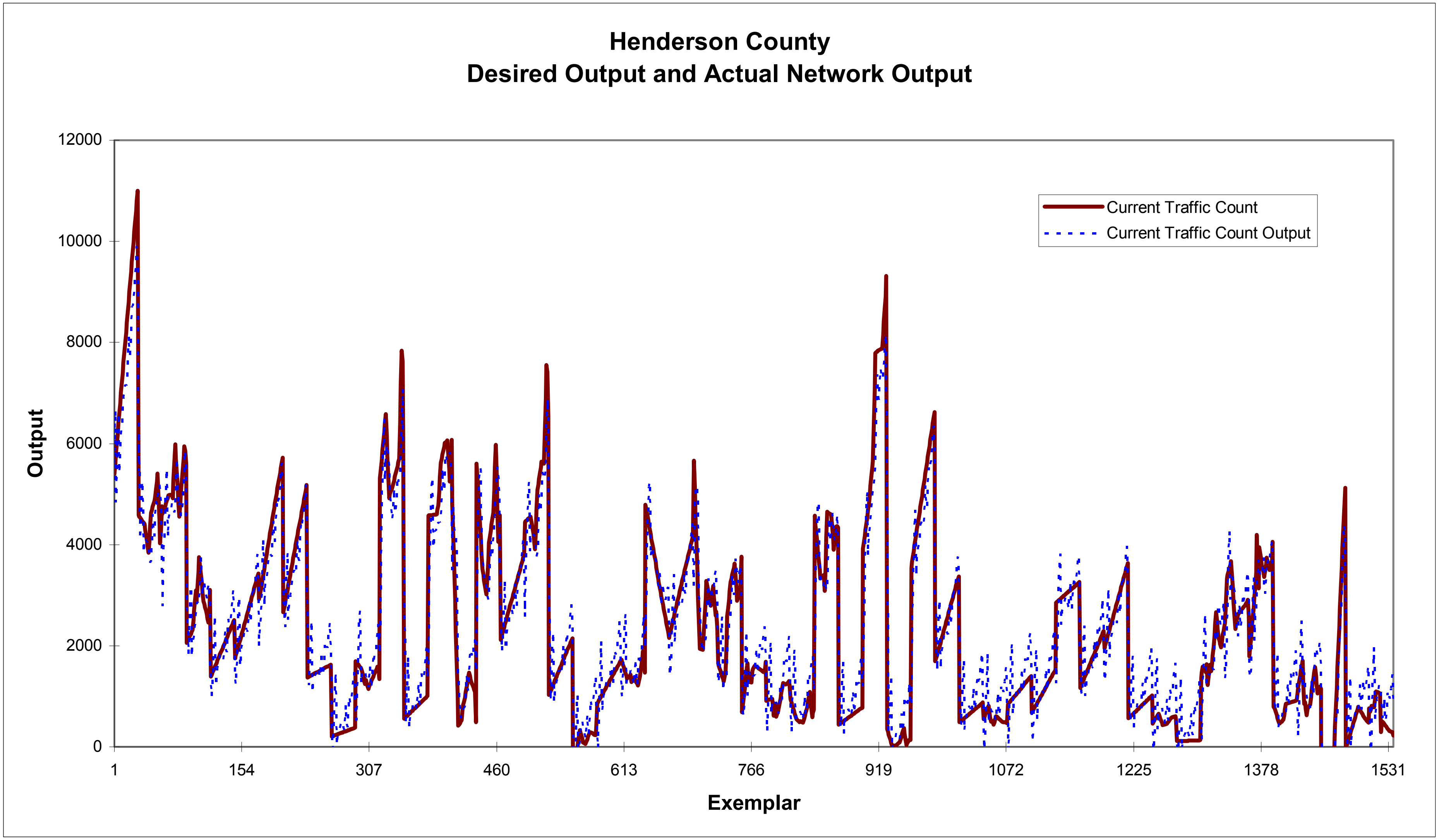
8.5 Fayette County Network Training Report.



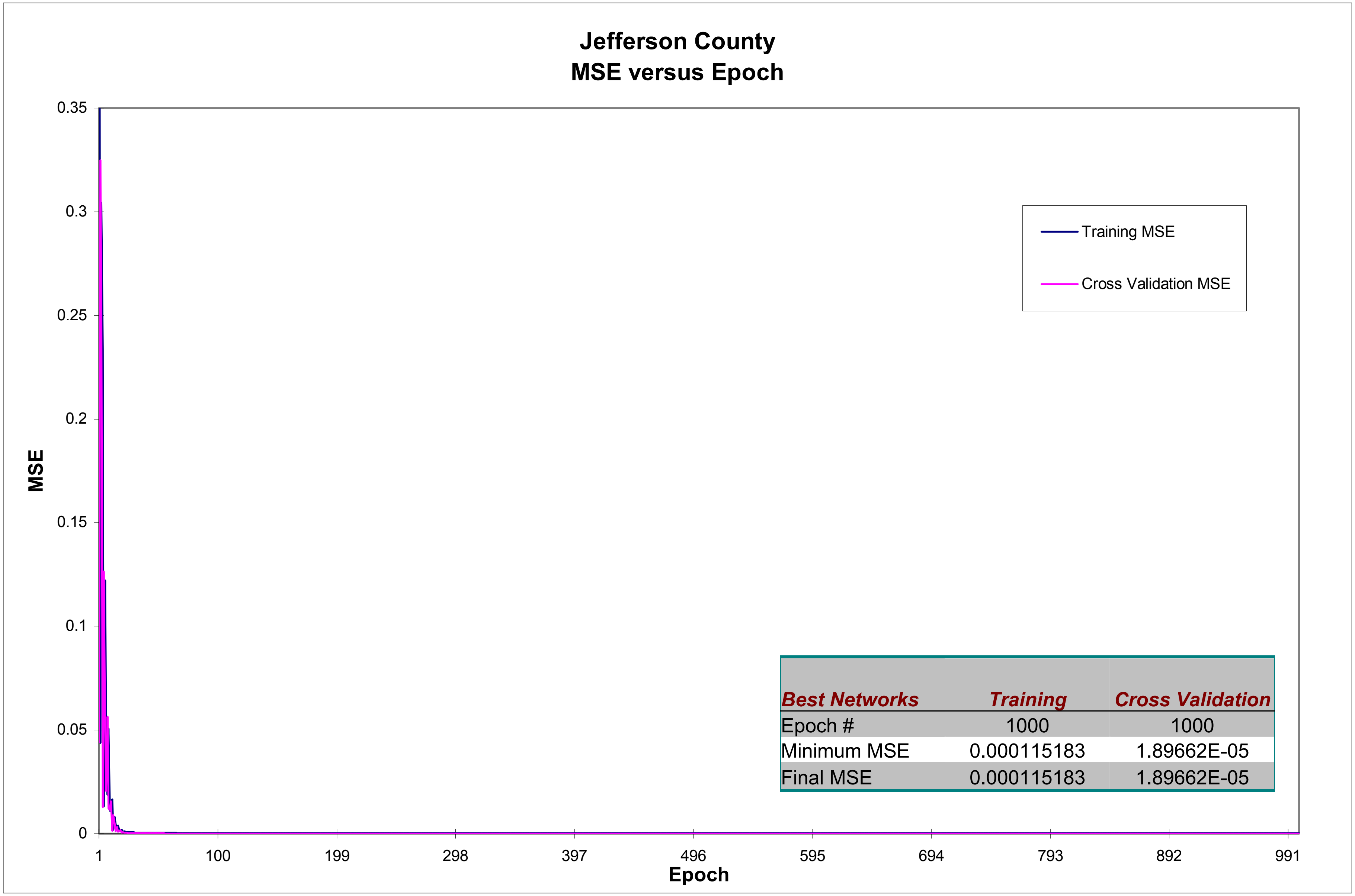
8.6 Fayette County Network Test Report.



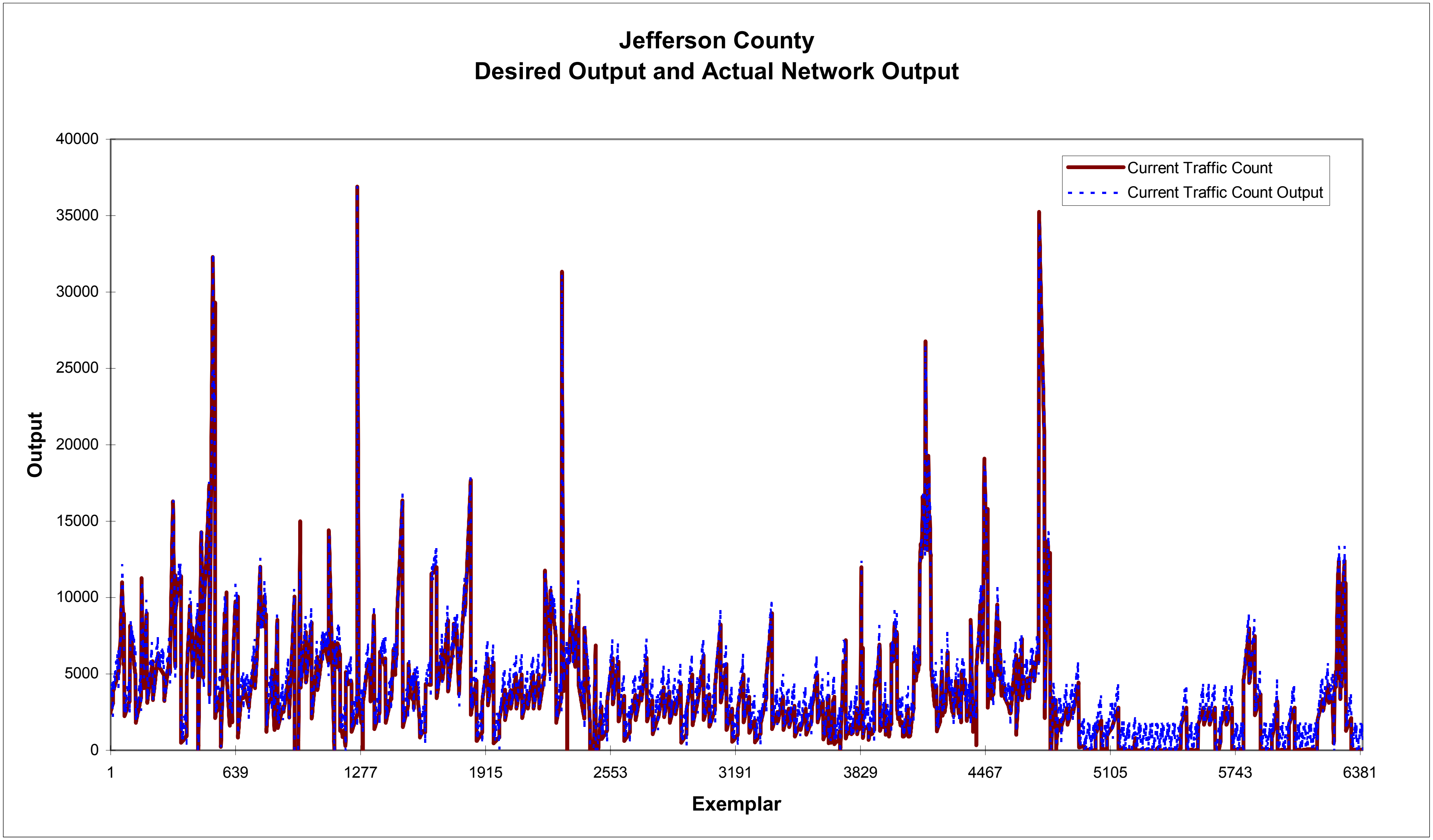
8.7 Henderson County Network Training Report.



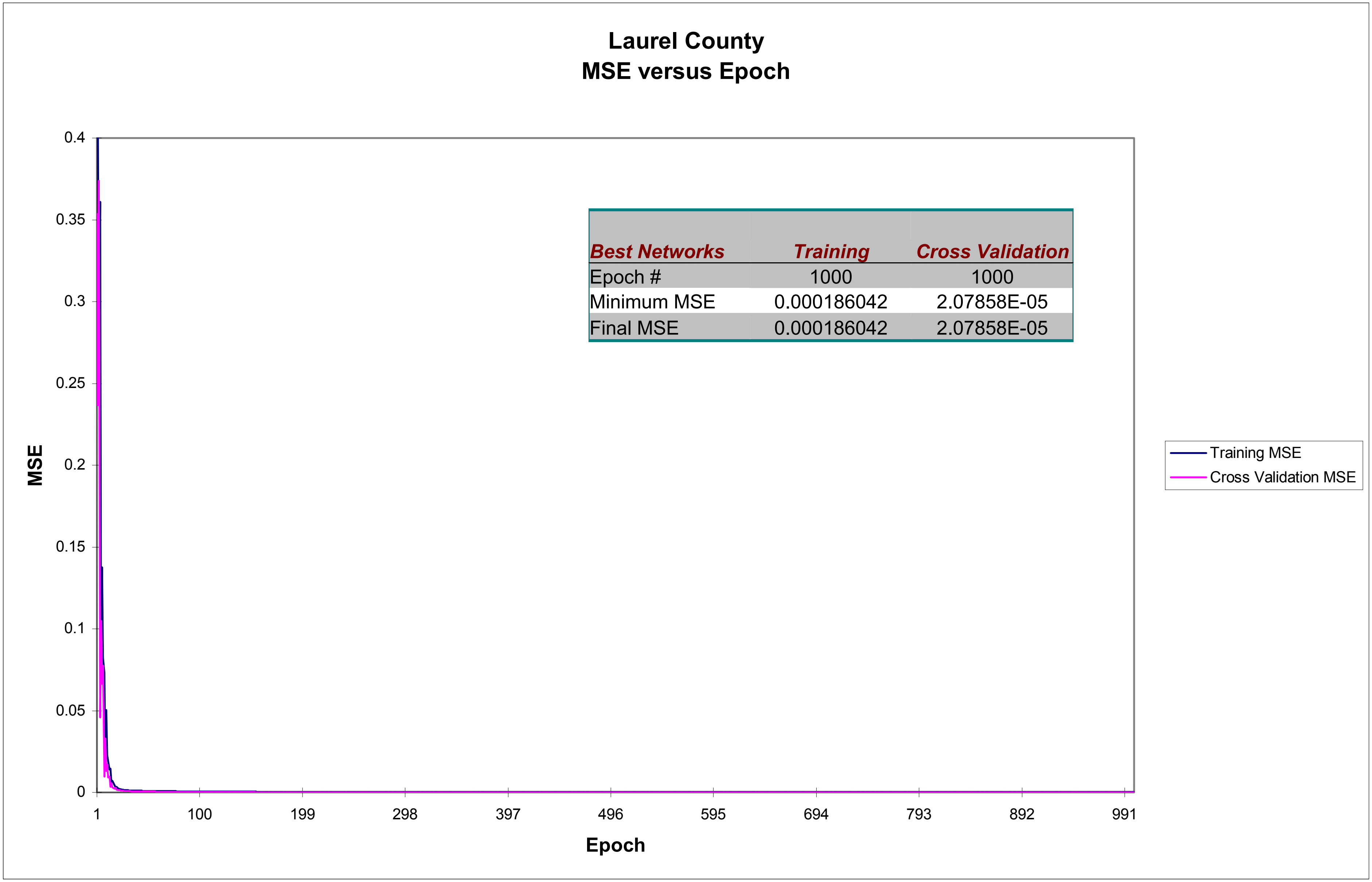
8.8 Henderson County Network Testing Report.



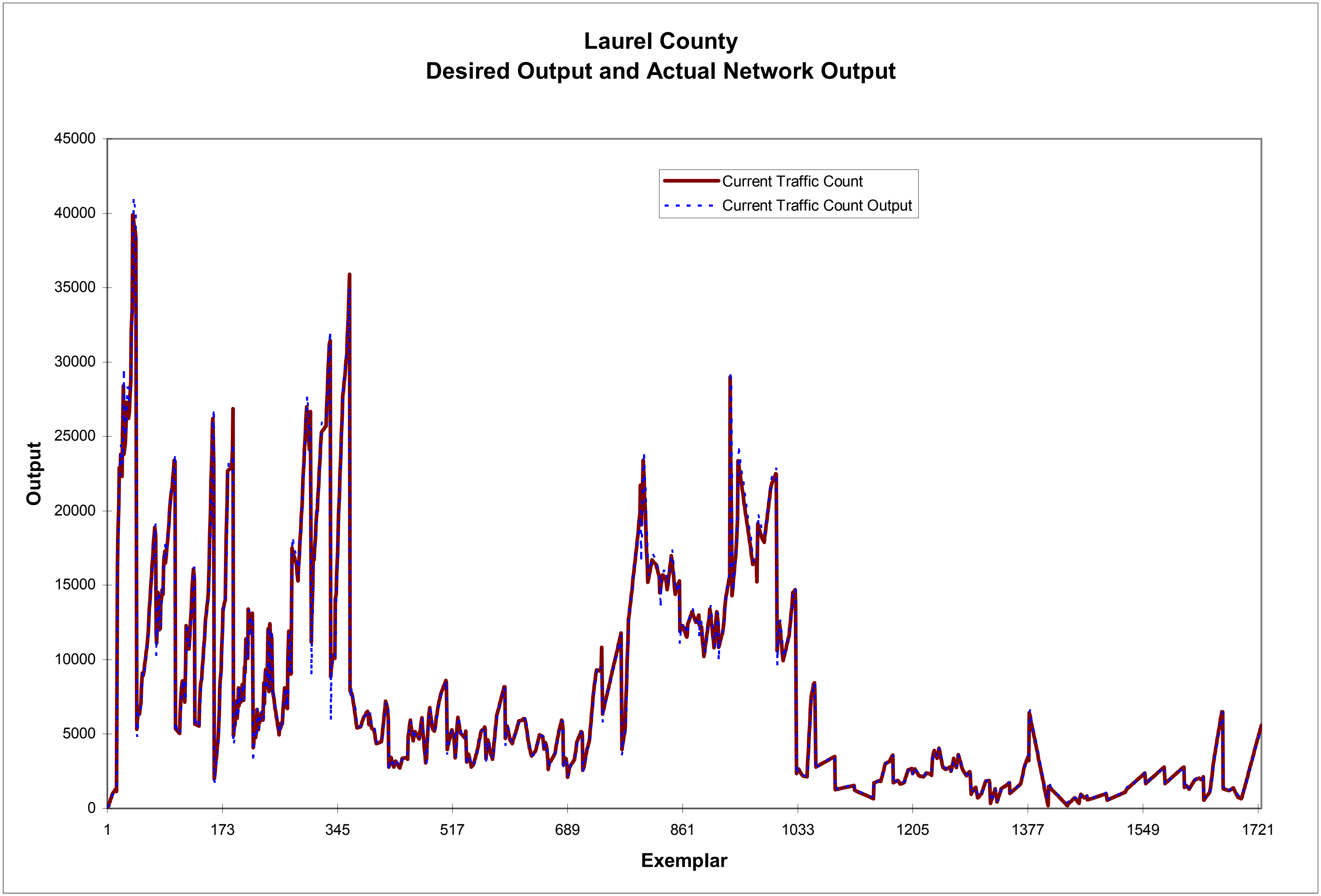
8.9 Jefferson County Network Training Report.



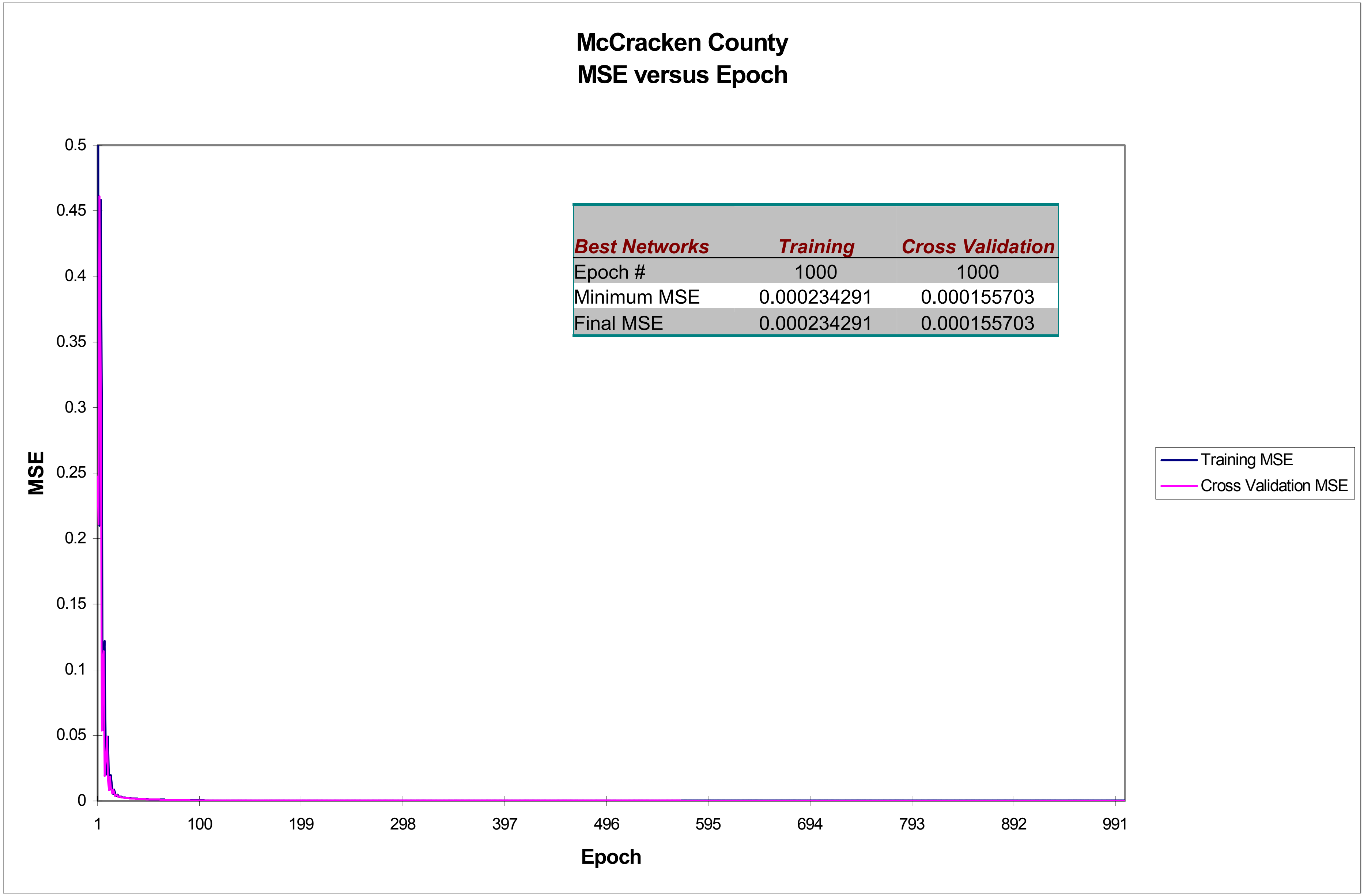
8.10 Jefferson County Network Testing Report.



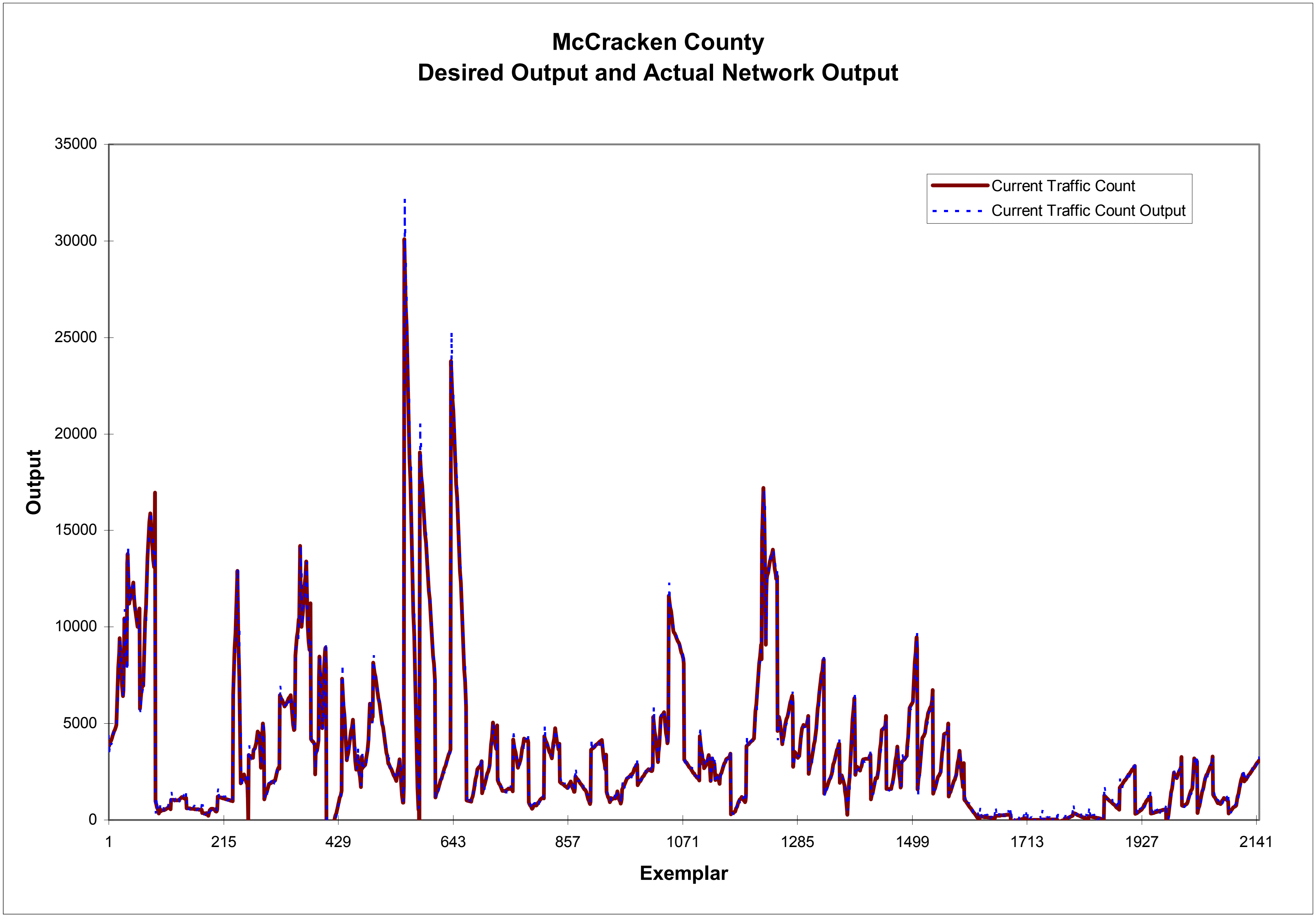
8.11 Laurel County Network Training Report.



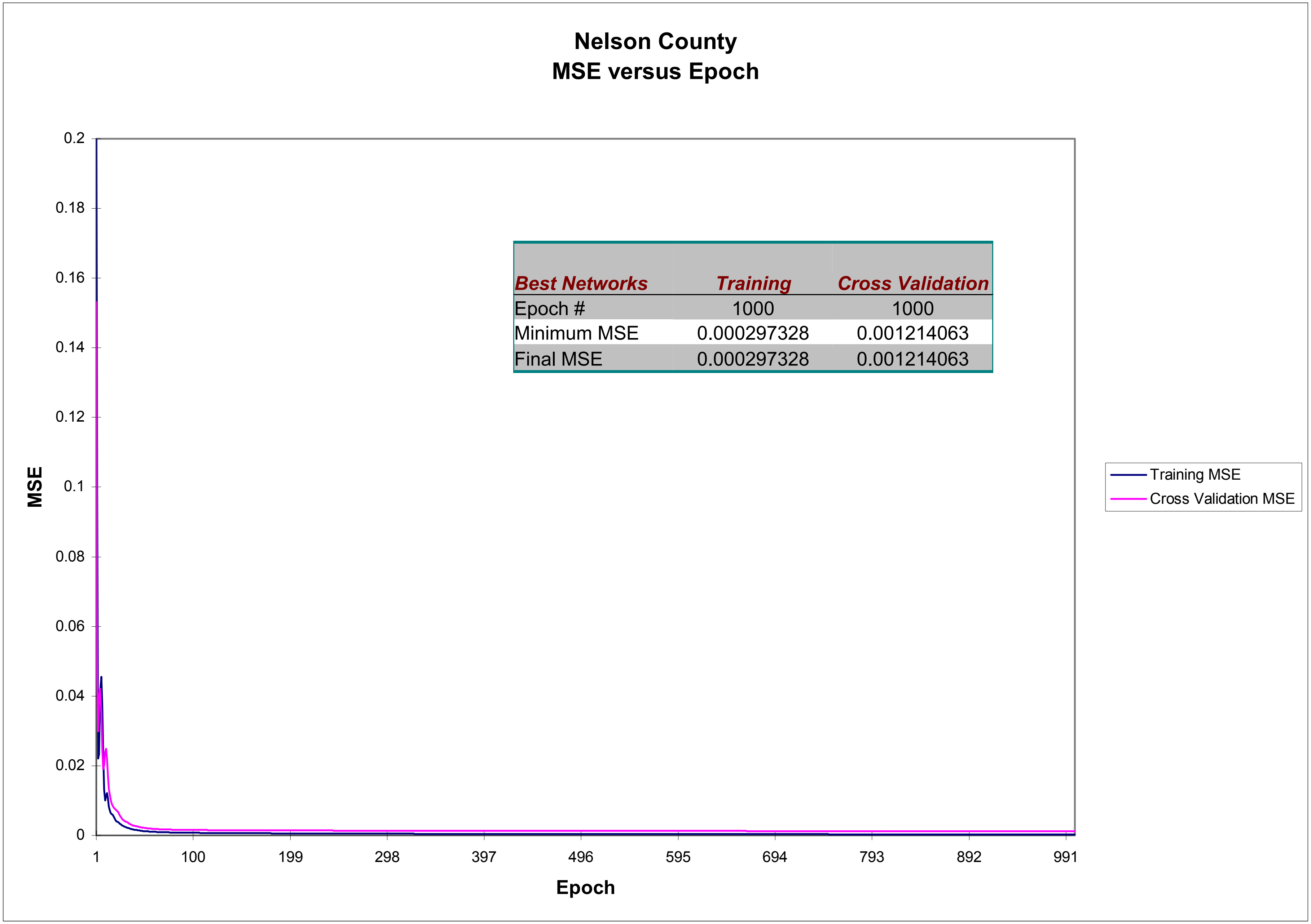
8.12 Laurel County Network Testing Report.



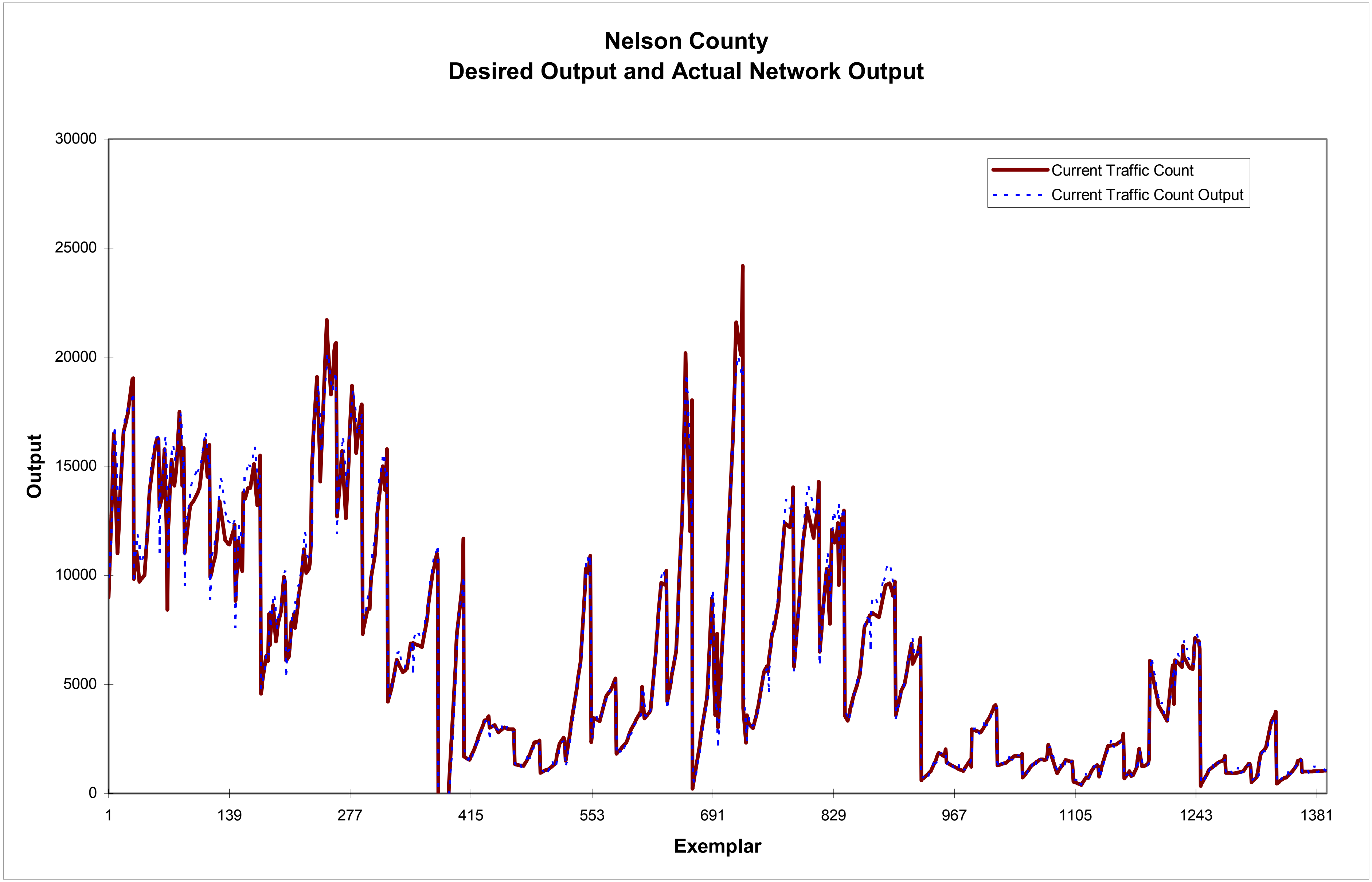
8.13 McCracken County Network Training Report.



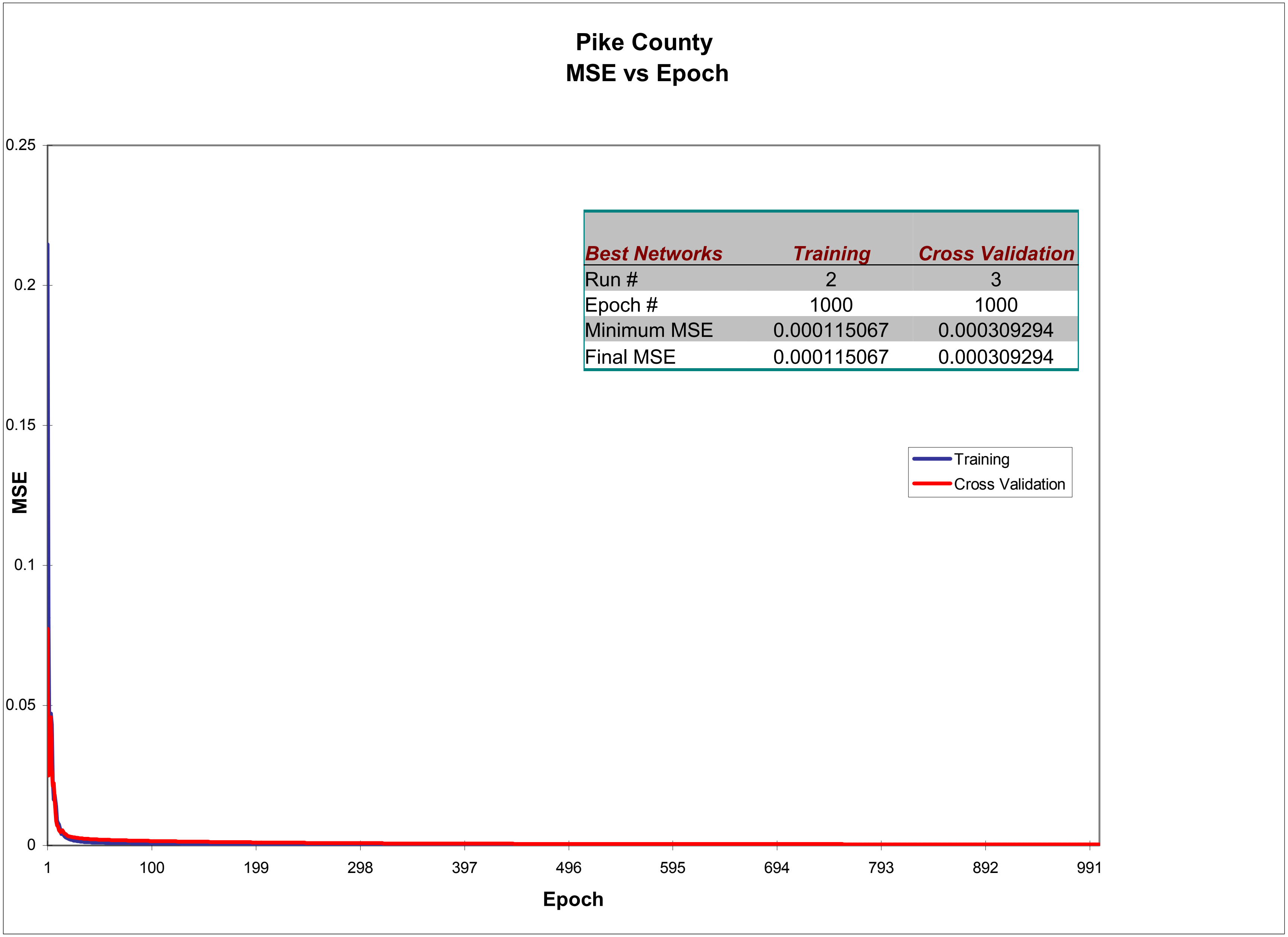
8.14 McCracken County Network Testing Report.



8.15 Nelson County Network Training Report.

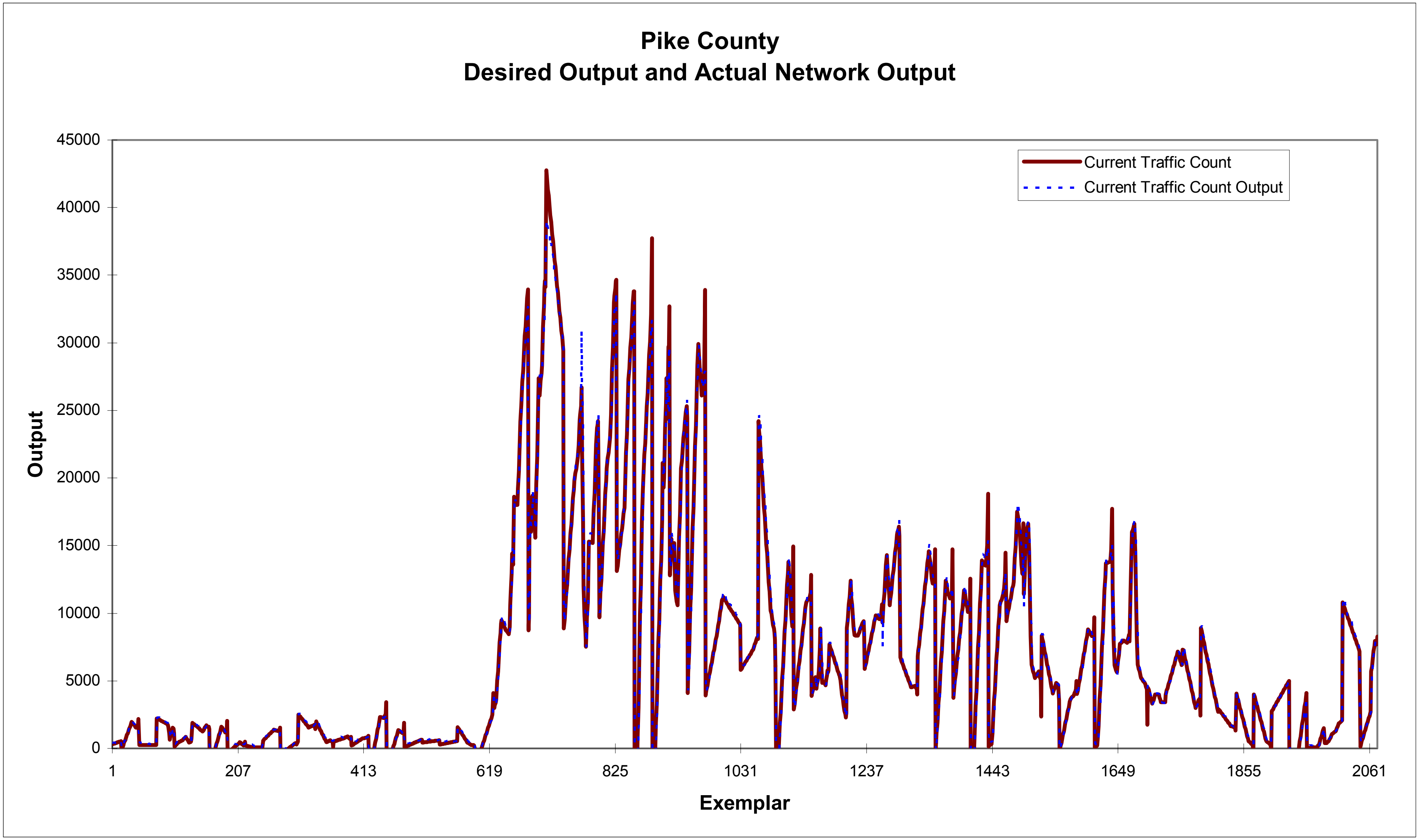


8.16 Nelson County Network Testing Report.

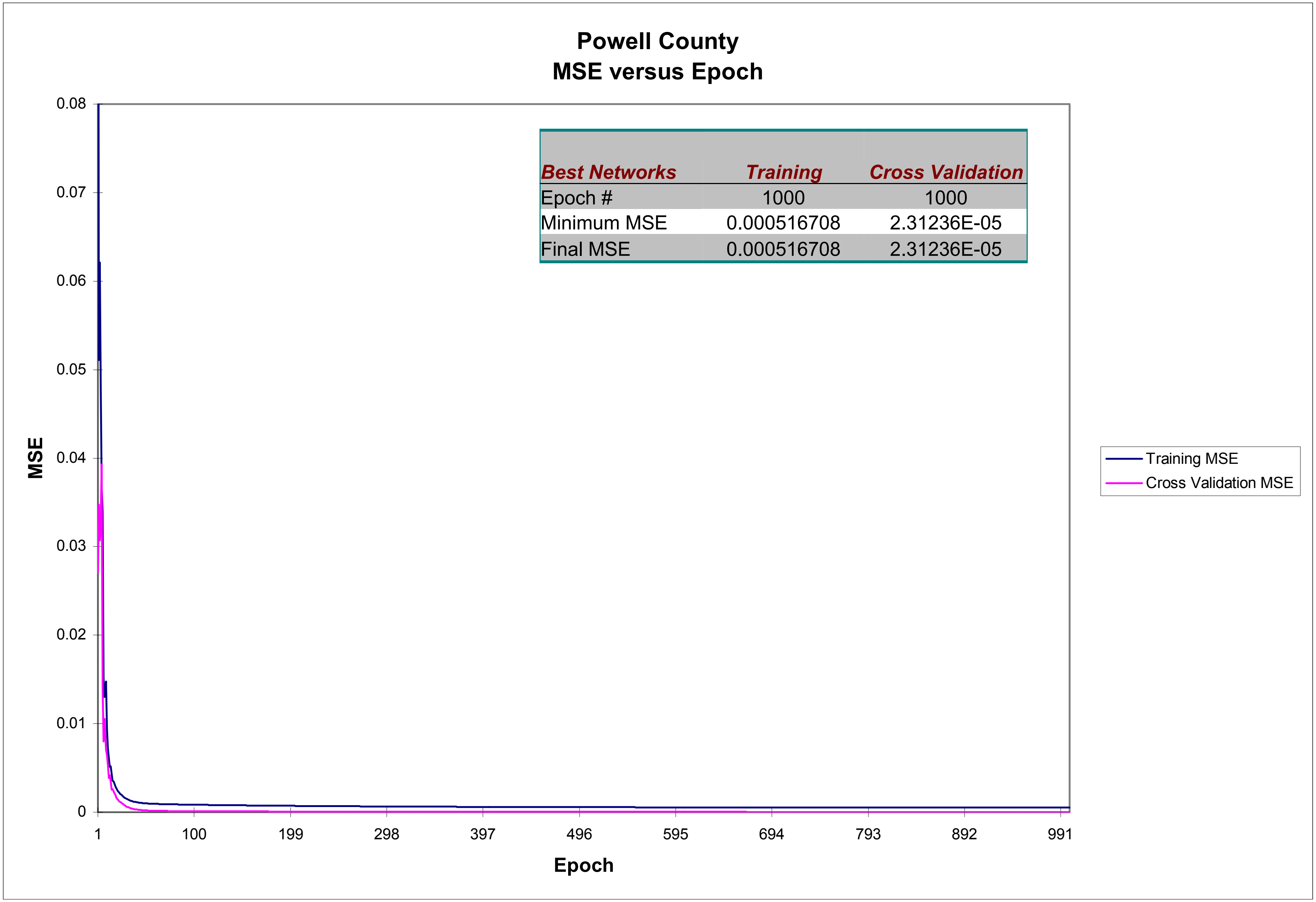


Best Networks	Training	Cross Validation
Run #	2	3
Epoch #	1000	1000
Minimum MSE	0.000115067	0.000309294
Final MSE	0.000115067	0.000309294

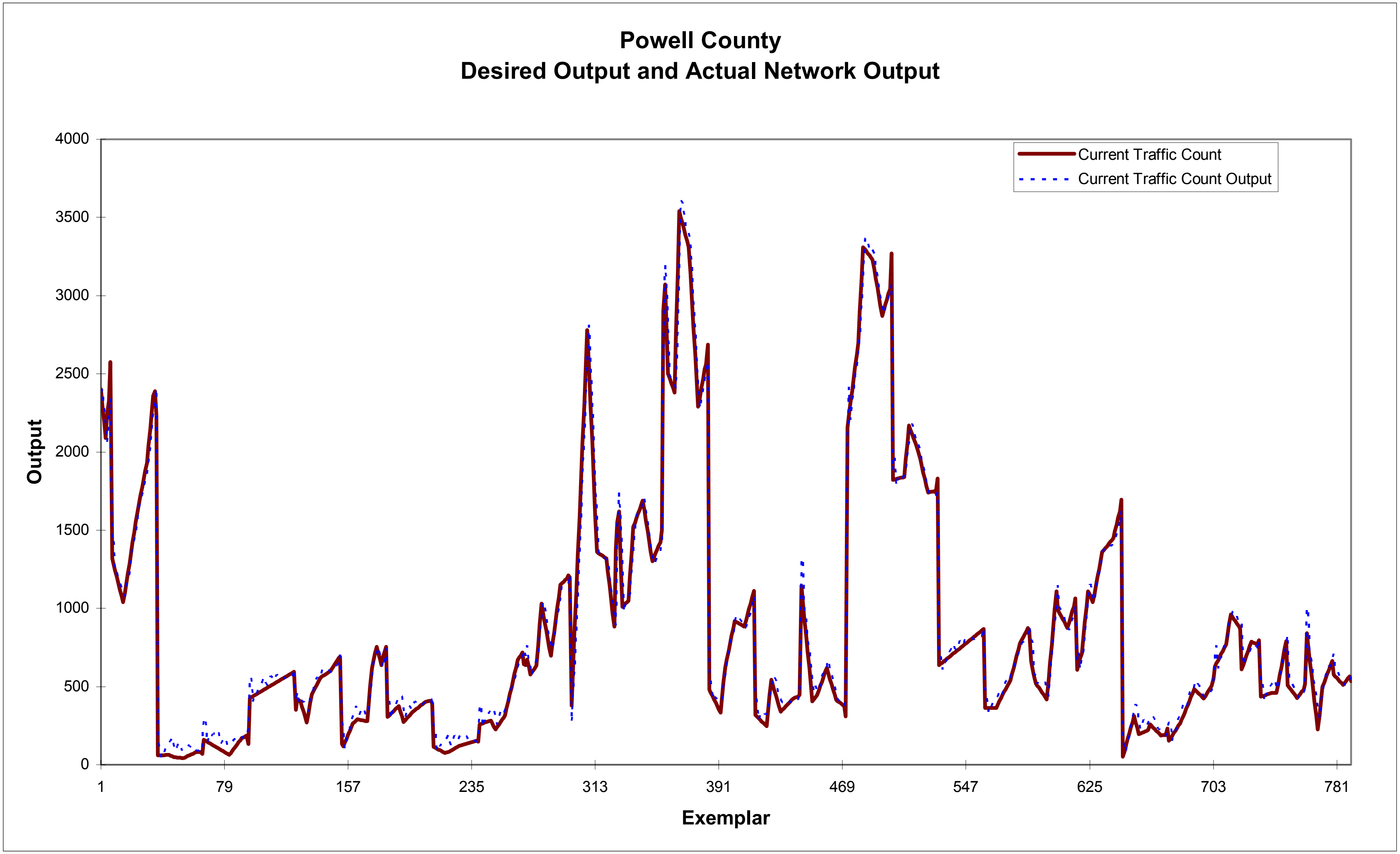
8.17 Pike County Network Training Report.



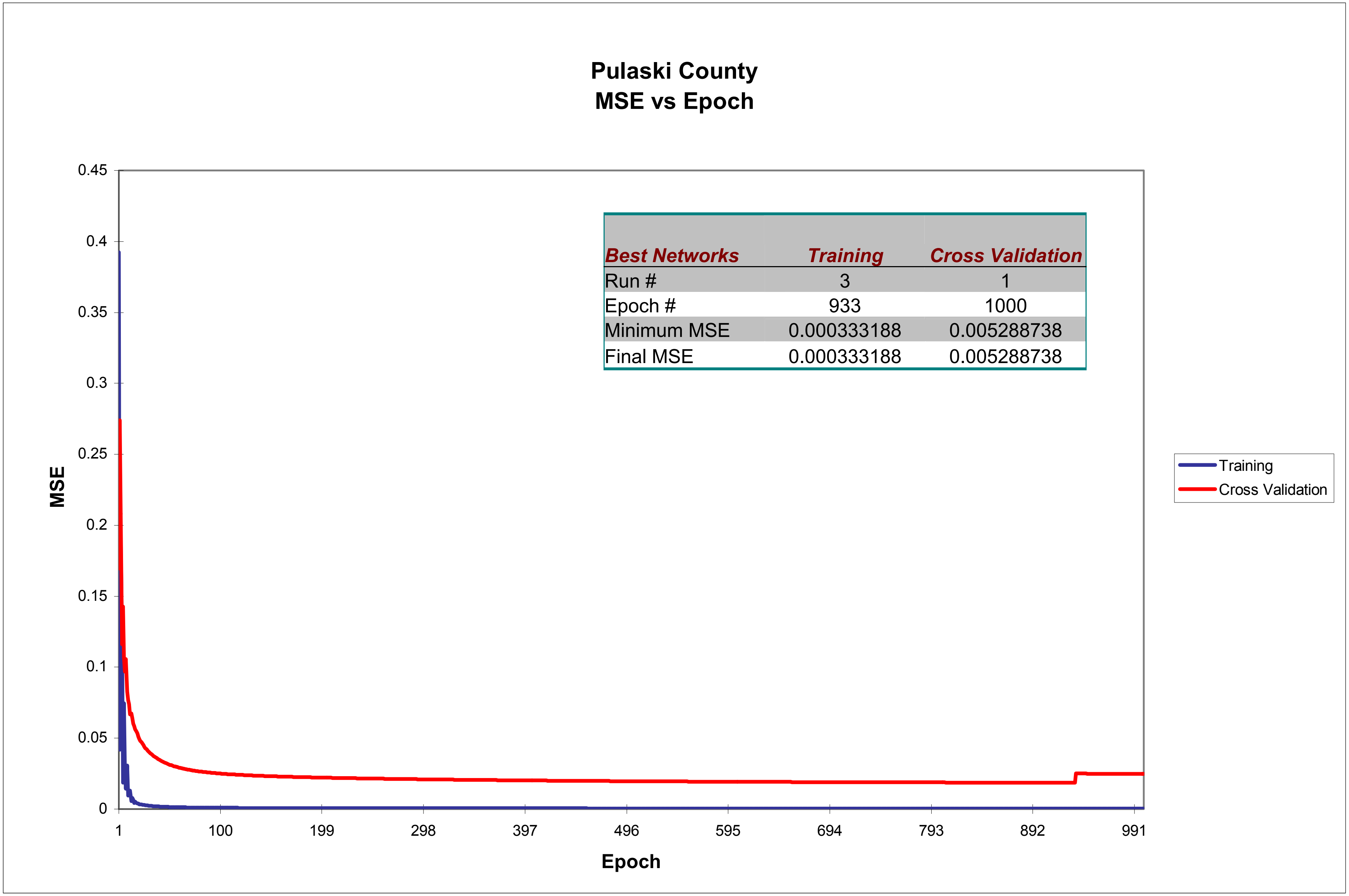
8.18 Pike County Network Testing Report.



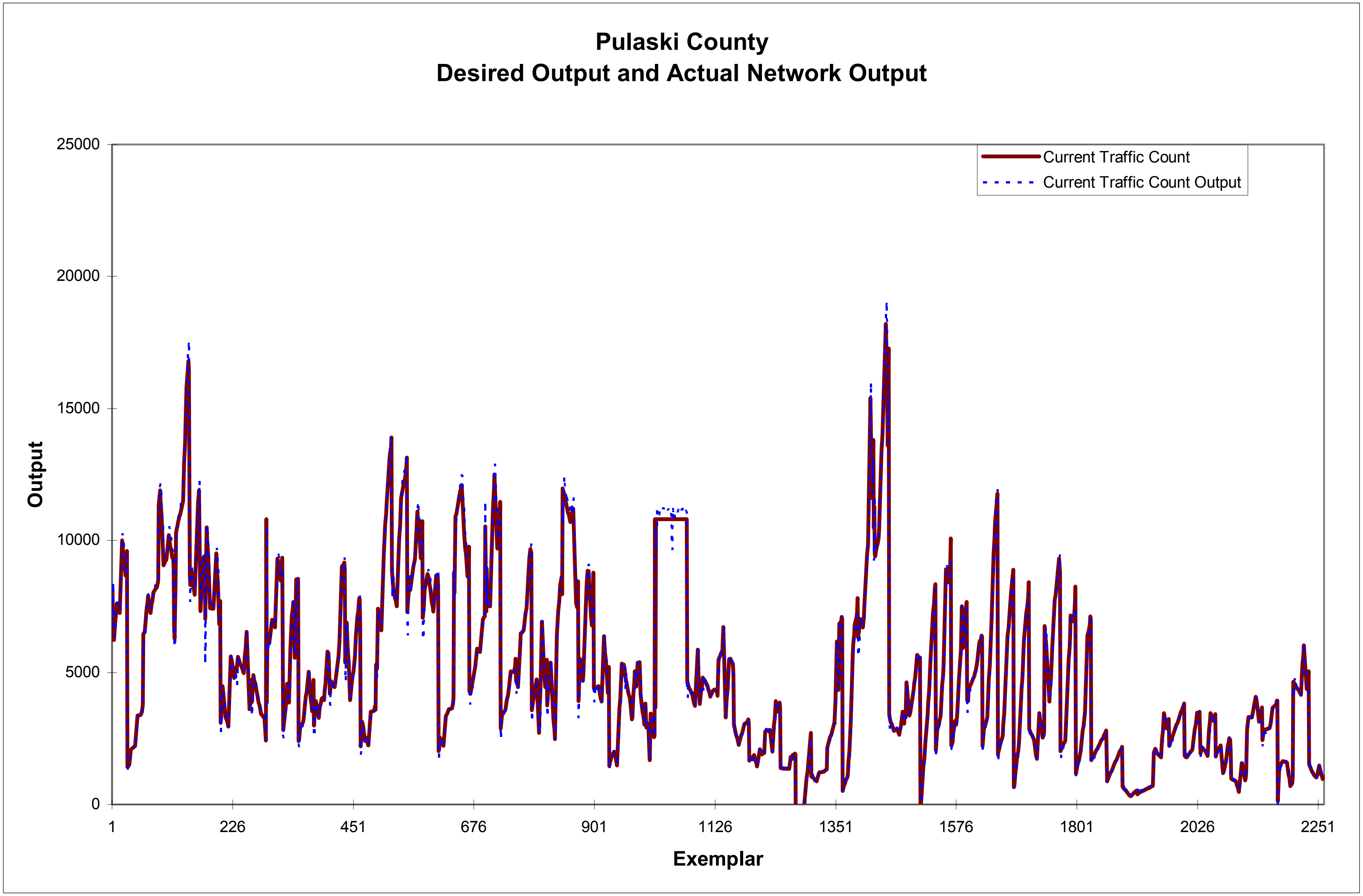
8.19 Powell County Network Training Report.



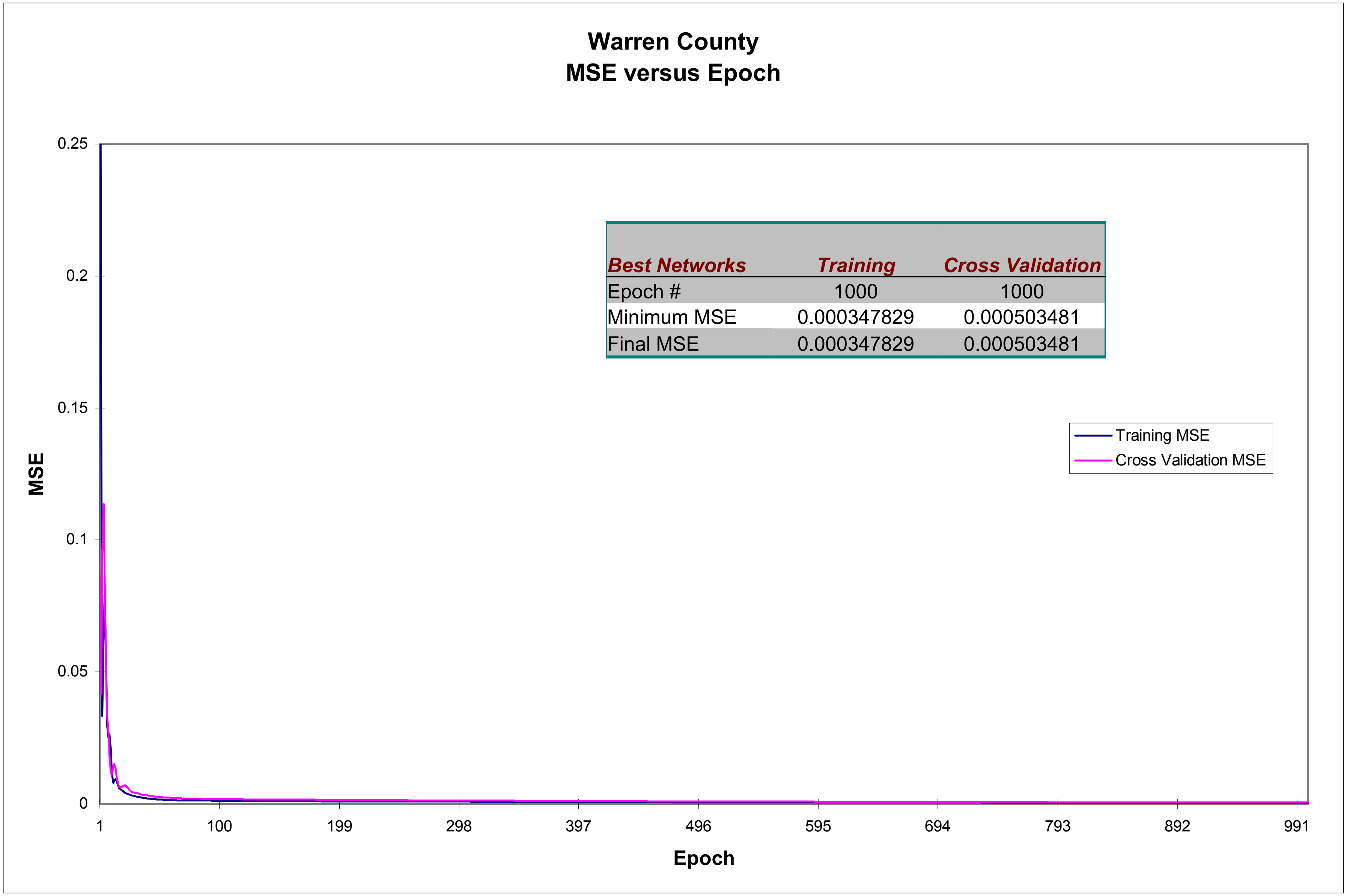
8.20 Powell County Network Testing Report.



8.21 Pulaski County Network Training Report.

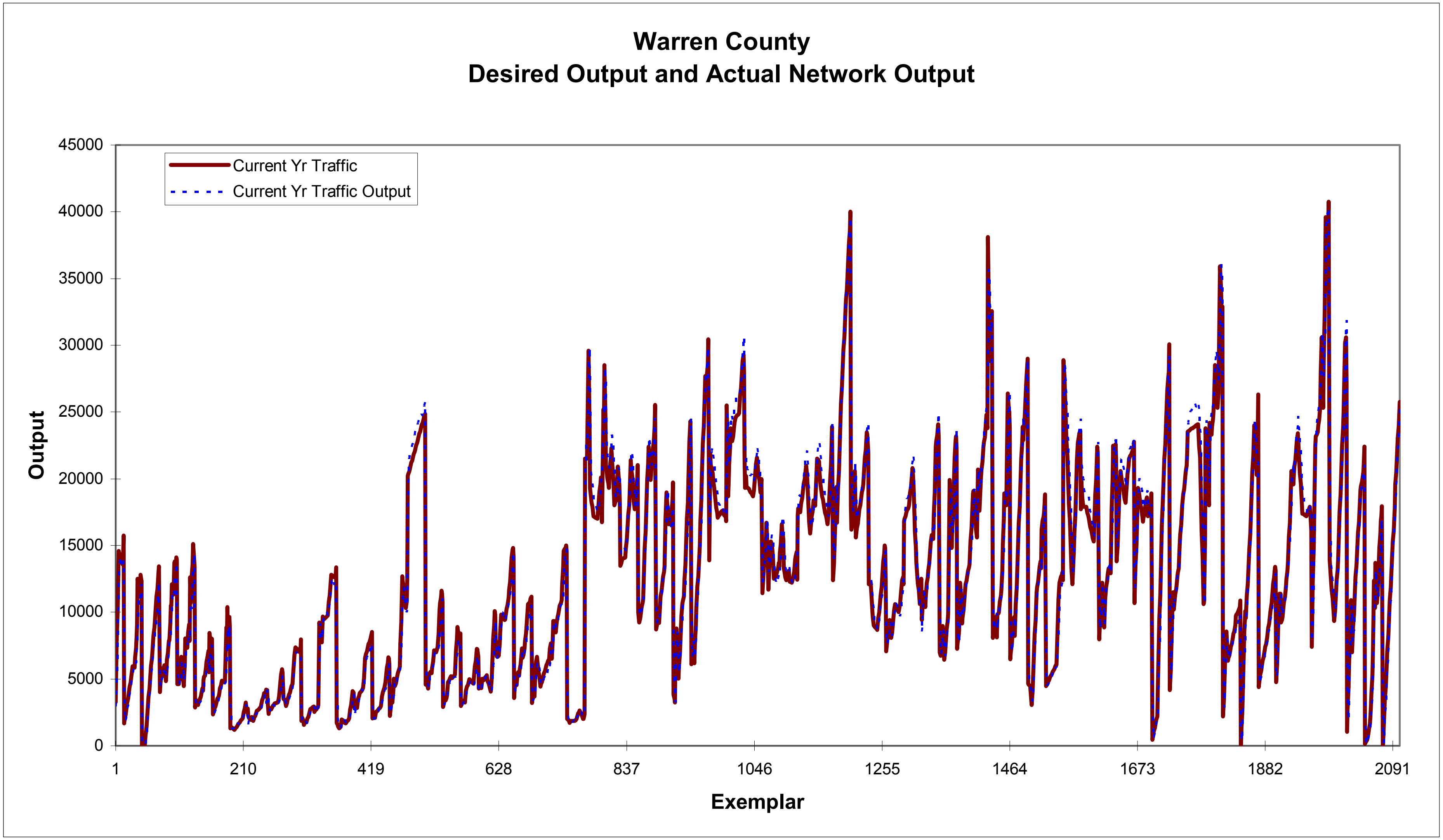


8.22 Pulaski County Network Testing Report.



Best Networks	Training	Cross Validation
Epoch #	1000	1000
Minimum MSE	0.000347829	0.000503481
Final MSE	0.000347829	0.000503481

8.23 Warren County Network Training Report.



8.24 Warren County Network Testing Report.

Kentucky County Population, 1990-2003

County	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Kentucky	3686892	3722380	3757867	3793355	3828843	3864331	3899818	3935306	3970794	4006281	4041769	4,090,381	4,129,298	4,168,366
Adair	15360	15546	15733	15919	16106	16292	16478	16665	16851	17038	17224	17,467	17,646	17,826
Allen	14628	14945	15262	15580	15897	16214	16531	16848	17166	17483	17800	18,284	18,680	19,087
Anderson	14571	15025	15479	15933	16387	16841	17295	17749	18203	18657	19111	19,767	20,303	20,848
Ballard	7902	7940	7979	8017	8056	8094	8132	8171	8209	8248	8286	8,363	8,424	8,484
Barren	34001	34404	34807	35211	35614	36017	36420	36823	37227	37630	38033	38,586	39,026	39,470
Bath	9692	9831	9971	10110	10249	10389	10528	10667	10806	10946	11085	11,271	11,421	11,574
Bell	31506	31361	31217	31072	30928	30783	30638	30494	30349	30205	30060	29,914	29,791	29,665
Boone	57589	60429	63269	66110	68950	71790	74630	77470	80311	83151	85991	90,265	93,787	97,413
Bourbon	19236	19248	19261	19273	19286	19298	19310	19323	19335	19348	19360	19,377	19,385	19,390
Boyd	51150	51010	50870	50731	50591	50451	50311	50171	50032	49892	49752	49,629	49,516	49,389
Boyle	25641	25847	26052	26258	26463	26669	26875	27080	27286	27491	27697	27,894	28,047	28,199
Bracken	7766	7817	7869	7920	7971	8023	8074	8125	8176	8228	8279	8,379	8,458	8,537
Breathitt	15703	15743	15782	15822	15862	15902	15941	15981	16021	16060	16100	16,185	16,247	16,307
Breckinridge	16312	16546	16779	17013	17246	17480	17714	17947	18181	18414	18648	18,998	19,280	19,562
Bullitt	47567	48934	50301	51668	53035	54402	55768	57135	58502	59869	61236	63,182	64,754	66,343
Butler	11245	11422	11598	11775	11951	12128	12304	12481	12657	12834	13010	13,294	13,523	13,756
Caldwell	13232	13215	13198	13180	13163	13146	13129	13112	13094	13077	13060	13,058	13,058	13,055
Calloway	30735	31079	31423	31768	32112	32456	32800	33144	33489	33833	34177	34,467	34,723	35,014
Campbell	83866	84341	84816	85291	85766	86241	86716	87191	87666	88141	88616	89,146	89,554	89,948
Carlisle	5238	5249	5261	5272	5283	5295	5306	5317	5328	5340	5351	5,374	5,392	5,411
Carroll	9292	9378	9465	9551	9637	9724	9810	9896	9982	10069	10155	10,309	10,434	10,560
Carter	24340	24595	24850	25105	25360	25615	25869	26124	26379	26634	26889	27,215	27,470	27,721
Casey	14211	14335	14458	14582	14705	14829	14953	15076	15200	15323	15447	15,623	15,763	15,903
Christian	68941	69273	69606	69938	70271	70603	70935	71268	71600	71933	72265	72,728	73,071	73,392
Clark	29496	29861	30226	30590	30955	31320	31685	32050	32414	32779	33144	33,629	34,011	34,389
Clay	21746	22027	22308	22589	22870	23151	23432	23713	23994	24275	24556	24,938	25,242	25,545
Clinton	9135	9185	9235	9285	9335	9385	9434	9484	9534	9584	9634	9,701	9,751	9,799
Crittenden	9196	9215	9234	9252	9271	9290	9309	9328	9346	9365	9384	9,421	9,450	9,478
Cumberland	6784	6820	6857	6893	6929	6966	7002	7038	7074	7111	7147	7,205	7,251	7,297
Daviess	87189	87625	88060	88496	88931	89367	89803	90238	90674	91109	91545	91,924	92,211	92,485
Edmonson	10357	10486	10614	10743	10872	11001	11129	11258	11387	11515	11644	11,831	11,980	12,130
Elliott	6455	6484	6514	6543	6572	6602	6631	6660	6689	6719	6748	6,793	6,828	6,865
Estill	14614	14683	14753	14822	14891	14961	15030	15099	15168	15238	15307	15,414	15,497	15,577
Fayette	225366	228881	232395	235910	239424	242939	246454	249968	253483	256997	260512	264,935	268,465	271,994

Kentucky County Population, 1990-2003

Fleming	12292	12442	12592	12742	12892	13042	13192	13342	13492	13642	13792	14,033	14,227	14,421
Floyd	43586	43472	43357	43242	43128	43014	42899	42785	42670	42556	42441	42,335	42,241	42,135
Franklin	44143	44497	44852	45206	45561	45915	46269	46624	46978	47333	47687	48,065	48,357	48,642
Fulton	8271	8219	8167	8115	8063	8011	7960	7908	7856	7804	7752	7,711	7,678	7,646
Gallatin	5393	5641	5888	6136	6384	6632	6879	7127	7375	7622	7870	8,257	8,579	8,912
Garrard	11579	11900	12222	12543	12864	13186	13507	13828	14149	14471	14792	15,280	15,681	16,091
Grant	15737	16402	17066	17731	18396	19061	19725	20390	21055	21719	22384	23,429	24,294	25,188
Graves	33550	33898	34246	34593	34941	35289	35637	35985	36332	36680	37028	37,498	37,877	38,261
Grayson	21050	21350	21651	21951	22251	22552	22852	23152	23452	23753	24053	24,490	24,842	25,195
Green	10371	10486	10600	10715	10830	10945	11059	11174	11289	11403	11518	11,666	11,784	11,903
Greenup	36742	36757	36772	36787	36802	36817	36831	36846	36861	36876	36891	36,965	37,011	37,047
Hancock	7864	7917	7970	8022	8075	8128	8181	8234	8286	8339	8392	8,474	8,538	8,601
Hardin	89240	89733	90227	90720	91214	91707	92200	92694	93187	93681	94174	94,944	95,555	96,167
Harlan	36574	36237	35900	35562	35225	34888	34551	34214	33876	33539	33202	32,832	32,528	32,220
Harrison	16248	16422	16595	16769	16942	17116	17289	17463	17636	17810	17983	18,269	18,498	18,731
Hart	14890	15146	15401	15657	15912	16168	16423	16679	16934	17190	17445	17,841	18,163	18,489
Henderson	43044	43223	43401	43580	43758	43937	44115	44294	44472	44651	44829	45,059	45,234	45,400
Henry	12823	13047	13270	13494	13718	13942	14165	14389	14613	14836	15060	15,396	15,666	15,938
Hickman	5566	5536	5505	5475	5444	5414	5384	5353	5323	5292	5262	5,226	5,198	5,170
Hopkins	46126	46165	46205	46244	46283	46323	46362	46401	46440	46480	46519	46,570	46,603	46,629
Jackson	11955	12109	12263	12417	12571	12725	12879	13033	13187	13341	13495	13,733	13,925	14,117
Jefferson	665123	667971	670819	673667	676515	679364	682212	685060	687908	690756	693604	696,983	699,589	702,113
Jessamine	30508	31361	32215	33068	33921	34775	35628	36481	37334	38188	39041	40,084	40,927	41,781
Johnson	23248	23268	23287	23307	23327	23347	23366	23386	23406	23425	23445	23,495	23,530	23,558
Kenton	142031	142974	143918	144861	145804	146748	147691	148634	149577	150521	151464	152,645	153,550	154,424
Knott	17906	17880	17855	17829	17803	17778	17752	17726	17700	17675	17649	17,611	17,577	17,539
Knox	29676	29888	30100	30312	30524	30736	30947	31159	31371	31583	31795	32,060	32,266	32,468
Larue	11679	11848	12018	12187	12357	12526	12695	12865	13034	13204	13373	13,614	13,808	14,003
Laurel	43438	44366	45293	46221	47149	48077	49004	49932	50860	51787	52715	53,980	54,998	56,023
Lawrence	13998	14155	14312	14469	14626	14784	14941	15098	15255	15412	15569	15,835	16,046	16,257
Lee	7422	7471	7521	7570	7620	7669	7718	7768	7817	7867	7916	7,984	8,040	8,097
Leslie	13642	13518	13394	13270	13146	13022	12897	12773	12649	12525	12401	12,243	12,114	11,982
Letcher	27000	26828	26655	26483	26311	26139	25966	25794	25622	25449	25277	25,119	24,985	24,846
Lewis	13029	13135	13242	13348	13454	13561	13667	13773	13879	13986	14092	14,274	14,420	14,565

Kentucky County Population, 1990-2003

Lincoln	20045	20377	20708	21040	21371	21703	22035	22366	22698	23029	23361	23,852	24,249	24,648
Livingston	9062	9136	9210	9285	9359	9433	9507	9581	9656	9730	9804	9,923	10,017	10,111
Logan	24416	24632	24847	25063	25279	25495	25710	25926	26142	26357	26573	26,908	27,178	27,449
Lyon	6624	6770	6915	7061	7206	7352	7498	7643	7789	7934	8080	8,247	8,384	8,525
McCracken	62879	63143	63406	63670	63933	64197	64460	64724	64987	65251	65514	65,788	65,996	66,196
McCreary	15603	15751	15898	16046	16194	16342	16489	16637	16785	16932	17080	17,334	17,537	17,738
McLean	9628	9659	9690	9721	9752	9783	9814	9845	9876	9907	9938	10,011	10,068	10,122
Madison	57508	58844	60181	61517	62854	64190	65526	66863	68199	69536	70872	72,343	73,553	74,805
Magoffin	13077	13103	13128	13154	13179	13205	13230	13256	13281	13307	13332	13,384	13,422	13,457
Marion	16499	16670	16842	17013	17184	17356	17527	17698	17869	18041	18212	18,428	18,603	18,780
Marshall	27205	27497	27789	28081	28373	28665	28957	29249	29541	29833	30125	30,478	30,760	31,042
Martin	12526	12531	12536	12542	12547	12552	12557	12562	12568	12573	12578	12,607	12,626	12,639
Mason	16666	16679	16693	16706	16720	16733	16746	16760	16773	16787	16800	16,840	16,868	16,892
Meade	24170	24388	24606	24824	25042	25260	25477	25695	25913	26131	26349	26,651	26,896	27,144
Menifee	5092	5238	5385	5531	5678	5824	5970	6117	6263	6410	6556	6,766	6,938	7,112
Mercer	19148	19315	19482	19649	19816	19983	20149	20316	20483	20650	20817	21,043	21,219	21,393
Metcalfe	8963	9070	9178	9285	9393	9500	9607	9715	9822	9930	10037	10,199	10,329	10,459
Monroe	11401	11437	11472	11508	11543	11579	11614	11650	11685	11721	11756	11,825	11,877	11,929
Montgomery	19561	19860	20160	20459	20758	21058	21357	21656	21955	22255	22554	22,979	23,319	23,661
Morgan	11648	11878	12108	12338	12568	12798	13028	13258	13488	13718	13948	14,247	14,491	14,742
Muhlenberg	31318	31370	31422	31474	31526	31579	31631	31683	31735	31787	31839	31,906	31,955	31,999
Nelson	29710	30487	31263	32040	32817	33594	34370	35147	35924	36700	37477	38,549	39,416	40,291
Nicholas	6725	6734	6743	6751	6760	6769	6778	6787	6795	6804	6813	6,829	6,841	6,851
Ohio	21105	21286	21467	21648	21829	22011	22192	22373	22554	22735	22916	23,197	23,424	23,654
Oldham	33263	34555	35846	37138	38429	39721	41012	42304	43595	44886	46178	48,099	49,658	51,237
Owen	9035	9186	9337	9489	9640	9791	9942	10093	10245	10396	10547	10,785	10,977	11,174
Owsley	5036	5018	5000	4983	4965	4947	4929	4911	4894	4876	4858	4,847	4,836	4,824
Pendleton	12036	12271	12507	12742	12978	13213	13448	13684	13919	14155	14390	14,760	15,063	15,371
Perry	30283	30194	30104	30015	29926	29837	29747	29658	29569	29479	29390	29,291	29,201	29,102
Pike	72584	72199	71814	71430	71045	70660	70275	69890	69506	69121	68736	68,319	67,954	67,562
Powell	11686	11841	11996	12151	12306	12462	12617	12772	12927	13082	13237	13,464	13,647	13,828
Pulaski	49489	50162	50835	51507	52180	52853	53526	54199	54871	55544	56217	57,095	57,796	58,494
Robertson	2124	2138	2152	2167	2181	2195	2209	2223	2238	2252	2266	2,285	2,299	2,313
Rockcastle	14803	14981	15159	15337	15515	15693	15870	16048	16226	16404	16582	16,842	17,050	17,259
Rowan	20353	20527	20701	20875	21049	21224	21398	21572	21746	21920	22094	22,166	22,231	22,309
Russell	14716	14876	15036	15196	15356	15516	15675	15835	15995	16155	16315	16,513	16,669	16,822

Kentucky County Population, 1990-2003

Scott	23867	24786	25706	26625	27545	28464	29383	30303	31222	32142	33061	34,337	35,385	36,462
Shelby	24824	25675	26527	27378	28229	29081	29932	30783	31634	32486	33337	34,577	35,596	36,641
Simpson	15145	15271	15397	15523	15649	15775	15901	16027	16153	16279	16405	16,573	16,706	16,838
Spencer	6801	7298	7794	8291	8787	9284	9780	10277	10773	11269	11766	12,595	13,298	14,040
Taylor	21146	21324	21502	21680	21858	22037	22215	22393	22571	22749	22927	23,097	23,230	23,363
Todd	10940	11043	11146	11249	11352	11456	11559	11662	11765	11868	11971	12,139	12,272	12,405
Trigg	10361	10585	10808	11032	11255	11479	11703	11926	12150	12373	12597	12,950	13,239	13,533
Trimble	6090	6294	6497	6701	6904	7108	7311	7515	7718	7921	8125	8,443	8,706	8,977
Union	16557	16465	16373	16281	16189	16097	16005	15913	15821	15729	15637	15,577	15,526	15,473
Warren	77720	79200	80680	82161	83641	85121	86601	88081	89562	91042	92522	94,338	95,810	97,303
Washington	10441	10489	10536	10584	10631	10679	10726	10774	10821	10869	10916	10,971	11,013	11,053
Wayne	17468	17714	17959	18205	18450	18696	18941	19187	19432	19678	19923	20,275	20,558	20,841
Webster	13955	13972	13988	14005	14021	14038	14054	14071	14087	14104	14120	14,180	14,227	14,272
Whitley	33326	33580	33834	34088	34342	34596	34849	35103	35357	35611	35865	36,196	36,455	36,710
Wolfe	6503	6559	6615	6672	6728	6784	6840	6896	6953	7009	7065	7,150	7,216	7,283
Woodford	19955	20280	20606	20931	21256	21582	21907	22232	22557	22883	23208	23,618	23,943	24,264

County		Training MSE	Epoch #		Cross Validation MSE	Epoch #		Testing NMSE	r
Adair		6.6562E-05	1000		6.6562E-05	1000		0.01228316	0.99493601
Allen		0.00043175	500		0.000431747	500		0.01413435	0.99293451
Anderson		0.00047763	1000		7.71064E-05	1000		0.01282763	0.9936389
Ballard		0.00015828	1000		0.000151137	1000		0.02037188	0.99052207
Barren		0.00021634	1000		0.000540327	1000		0.03008684	0.98680951
Bath		0.00019662	1000		8.65327E-05	1000		0.03558811	0.98474568
Bell		0.00026911	1000		7.99266E-05	1000		0.01062248	0.99476474
Boone		0.00016847	1000		0.001337097	1000		0.05909235	0.97558501
Bourbon		0.00042175	1000		0.001058012	1000		0.00835226	0.99627252
Boyd		0.0002168	1000		0.000128167	1000		0.017758	0.99120686
Boyle		0.00031395	1000		0.003035921	1000		0.03192785	0.99227044
Bracken		7.4458E-05	1000		2.92875E-05	1000		0.01279361	0.99442812
Breathitt		0.00022949	1000		1.86778E-05	1000		0.00934049	0.99561955
Breckinridge		0.00017281	1000		0.000459096	1000		0.04854958	0.97542771
Bullitt		9.2281E-05	1000		3.9283E-05	1000		0.02567509	0.98759102
Butler		0.00103196	1000		0.009441281	224		0.02286416	0.98937503
Caldwell		0.00023261	1000		0.000324055	1000		0.03850533	0.9807057
Calloway		0.00022141	1000		0.000540981	1000		0.04331745	0.98561415
Campbell		0.00020669	1000		3.55644E-05	1000		0.01810046	0.99133358
Carlisle		0.00019376	1000		0.000286051	1000		0.01261476	0.99428532
Carroll		0.00012877	1000		2.9131E-05	1000		0.00858956	0.99605665
Carter		0.00011557	1000		0.000724678	1000		0.0100527	0.99551006
Casey		0.00042355	1000		3.49143E-05	1000		0.03624724	0.98590175
Christian		0.00021175	1000		0.001059957	1000		0.01438385	0.99319668
Clark		0.00017489	1000		0.000338221	1000		0.01602014	0.99260019
Clay		0.00017298	1000		6.13847E-05	1000		0.00724942	0.99674685
Clinton		0.00016171	1000		0.000205756	1000		0.05697444	0.98735261
Crittenden		0.00018938	1000		*	*		0.00463285	0.99768289
Cumberland		0.00018147	1000		*	*		0.00607579	0.99695764
Daviess		0.00011403	1000		6.35016E-05	1000		0.02695375	0.98835323
Edmonson		0.0003792	1000		8.59928E-05	1000		0.01865632	0.99115236
Elliott		0.00053957	1000		0.000806484	1000		0.02202794	0.99552761
Estill		0.00014634	1000		0.002810084	1000		0.00944821	0.99560386
Fayette		0.00014025	794		0.000149314	871		0.0117376	0.9945306
Fleming		0.00017483	1000		4.64786E-05	1000		0.01548374	0.99465811
Floyd		0.00020083	1000		0.000340304	1000		0.01709101	0.99312715
Franklin		0.00064451	1000		0.0010008	1000		0.04145856	0.97963636
Fulton		0.00036675	1000		0.006307511	1000		0.0070656	0.9964612
Gallatin		0.00062745	1000		9.10333E-06	1000		0.02524074	0.98895479
Garrard		0.00022236	1000		*	*		0.0029987	0.99849962
Grant		0.00011801	1000		*	*		0.00663567	0.9966775
Graves		0.00011545	1000		3.3311E-05	1000		0.0194926	0.99041653
Grayson		0.00012577	1000		0.001538955	566		0.03582271	0.98879457
Green		9.9969E-05	1000		*	*		0.00293332	0.99853315
Greenup		8.6779E-05	1000		0.000299818	1000		0.00779719	0.99611464
Hancock		0.0005378	1000		0.000483488	1000		0.03782214	0.99095731

County		Training MSE	Epoch #		Cross Validation MSE	Epoch #		Testing NMSE	r
Hardin		3.2851E-05	1000		*	*		0.01254924	0.99370629
Harlan		0.00019674	1000		0.00019279	1000		0.0217376	0.9899921
Harrison		0.0001684	1000		0.000474155	1000		0.01736174	0.99151081
Hart		0.00034018	1000		1.92824E-05	1000		0.31143495	0.91370734
Henderson		0.00117911	1000		0.000595602	1000		0.09324007	0.9551776
Henry		0.00017341	1000		0.0001063	1000		0.06211372	0.97580898
Hickman		0.00088713	1000		0.000125777	1000		0.03350434	0.9864367
Hopkins		0.00038332	1000		0.001992642	1000		0.08819235	0.9560219
Jackson		9.6265E-05	1000		*	*		0.00402878	0.99798362
Jefferson		0.00011518	1000		1.89662E-05	1000		0.06536398	0.97952127
Jessamine		0.00014052	1000		0.000610157	1000		0.00649242	0.99688584
Johnson		0.00058652	1000		0.000166915	1000		0.01898502	0.99079738
Kenton		0.00027079	1000		5.63324E-05	1000		0.01717009	0.99148145
Knott		0.00068282	1000		0.000453995	1000		0.03099585	0.98470933
Knox		0.00017818	1000		0.001017905	1000		0.02942023	0.98869977
Larue		7.8898E-05	1000		0.002420958	1000		0.01534792	0.99265601
Laurel		0.00018604	1000		2.07858E-05	1000		0.00946087	0.99530384
Lawrence		0.00080036	1000		0.000188116	1000		0.0114573	0.99573121
Lee		0.00025409	1000		0.000140089	1000		0.03310105	0.99163143
Leslie		0.00062375	1000		0.000419102	1000		0.02660632	0.98781664
Letcher		0.000296	1000		0.000105854	1000		0.03253756	0.9854965
Lewis		0.00029454	1000		0.000119158	1000		0.0475607	0.98520442
Lincoln		0.00043904	1000		1.64022E-05	1000		0.01181606	0.9942117
Livingston		0.00031281	1000		*	*		0.0113857	0.99429755
Logan		0.00073084	1000		0.003572436	1000		0.02374463	0.98882005
Lyon		0.00017152	1000		*	*		0.01088421	0.99454354
McCracken		0.00023429	1000		0.000155703	1000		0.0119607	0.99423759
McCreary		0.00011358	1000		*	*		0.00697955	0.99650529
McLean		0.00028538	1000		*	*		0.0063444	0.996823
Madison		0.00016289	1000		0.00084434	1000		0.01760429	0.99136414
Magoffin		0.00026859	1000		*	*		0.00890538	0.99553796
Marion		0.00034894	1000		*	*		0.01560733	0.9921894
Marshall		0.00043452	1000		5.25548E-05	1000		0.05390334	0.9755516
Martin		0.00050985	1000		0.000267003	1000		0.00591249	0.99768016
Mason		0.00023133	1000		0.000436353	1000		0.02412563	0.99017166
Meade		0.00012049	1000		*	*		0.0036435	0.99817664
Menifee		0.00030873	1000		*	*		0.00583937	0.99707611
Mercer		7.9251E-05	1000		0.005871758	1000		0.02258397	0.99248835
Metcalfe		0.00028148	1000		*	*		0.00804867	0.99596755
Monroe		0.00028148	1000		0.002571351	266		0.0096619	0.99537939
Montgomery		0.0003273	1000		0.001253514	1000		0.01068984	0.99584523
Morgan		0.00023347	1000		6.23185E-05	1000		0.01784967	0.99248288
Muhlenberg		0.00038133	1000		0.00011377	1000		0.01990127	0.99226383
Nelson		0.00029733	1000		0.001214063	1000		0.01551197	0.99274689
Nicholas		0.00028941	1000		2.30399E-05	1000		0.05639121	0.97572497
Ohio		0.00037687	1000		2.78366E-05	1000		0.15686544	0.9867592

County		Training MSE	Epoch #		Cross Validation MSE	Epoch #		Testing NMSE	R
Oldham		0.00046505	1000		6.30966E-05	1000		0.01266744	0.99560927
Owen		0.00010114	1000		7.04148E-05	1000		0.00921765	0.99548806
Owsley		0.00021303	1000		0.000575411	1000		0.01281669	0.99372405
Pendleton		6.4857E-05	1000		6.37921E-05	892		0.0182638	0.99723959
Perry		0.00069215	1000		0.004423496	591		0.01707179	0.9917094
Pike		0.00011507	1000		0.000309294	1000		0.00863796	0.99577872
Powell		0.00051671	1000		2.31236E-05	1000		0.01067515	0.99505336
Pulaski		0.00033319	933		0.005288738	1000		0.02129127	0.98982798
Robertson		0.00046448	1000		0.003814906	1000		0.00821387	0.99588532
Rockcastle		0.00022601	1000		3.75931E-05	1000		0.04264146	0.98578186
Rowan		0.0003088	1000		0.005889977	1000		0.01793162	0.99213309
Russell		0.00011349	1000		0.001737266	1000		0.00583538	0.99718207
Scott		0.00018405	1000		0.000675299	1000		0.00796566	0.99625756
Shelby		0.00023074	1000		1.17608E-05	1000		0.005091	0.99747321
Simpson		0.00010836	1000		0.000308596	1000		0.0079721	0.99635654
Spencer		0.00043934	1000		0.000228509	1000		0.03543127	0.99268102
Taylor		8.7557E-05	1000		*	*		0.01073397	0.99462554
Todd		0.00044861	1000		2.64147E-05	964		0.02419465	0.99175512
Trigg		0.00035946	1000		2.08082E-05	1000		0.00497867	0.99760798
Trimble		0.00063186	1000		5.79979E-05	1000		0.05197099	0.98202408
Union		0.00201719	1000		7.43644E-05	1000		0.04857815	0.97920148
Warren		0.00034783	1000		0.000503481	1000		0.03535105	0.98355144
Washington		0.00033479	1000		2.28558E-05	1000		0.01126003	0.99510126
Wayne		0.00020022	1000		0.000132627	1000		0.0169322	0.99491389
Webster		0.00026057	1000		*	*		0.01178701	0.99408917
Whitley		0.00031675	1000		0.001104976	1000		0.03462913	0.98635245
Wolfe		0.00071938	1000		6.05598E-05	1000		0.01238308	0.99557776
Woodford		0.00015501	1000		*	*		0.00574869	0.99712169

* All data used as training.