Fault Detection of Brahmanbaria Gas Plant using Neural Network

M.T. Sowgath,[1,*] and S Ahmed[2]

[1] Assistant Professor, Chemical Engineering Department, BUET
Dhaka, Bangladesh

[2]Senior Gas Plant Operations Specialist, Chevron Bangladesh Ltd, Bangladesh

[*]mstanvir@che.buet.ac.bd

Abstract—**In recent years, several accidents in pioneer gas processing industries led industries to put emphasis on real-time fault detection. Neural Network (NN) based fault (abnormal situation) detection technique played an important role in monitoring industrial safety. In this work, an attempt has been made to study the fault detection of Brahmanbaria gas processing plant using multi layered feed forward NN based system. NN based fault detection system is trained, validated and tested using data generated using the dynamic model. Preliminary results show that NN based method is able to detect the faults of Brahmanbaria Gas processing plant for fewer no of faults.**[*]

***Index Terms*— Neural Network, Fault detection, GasProcessing Plant, Industrial Safety Management.**

I. Introduction

Natural gas (NG) plays an important role in different sectors such as power generation sector, fertilizer, industrial and commercial sector in Bangladesh [1-2]. There are many gas producing fields in Bangladesh. Although process safety technology has been gradually implemented over the years, several accidents happened in gas field industry in Bangladesh like BGFCL, Nikko, Occidental, Tullow, and Chevron. Massive blowout took place in Occidental and the similar incident happened at Tengratila by Nikko. Major gas leakage was found in Titas Gas Field (BGFCL) [3-5]. Still, the process plants face difficulties due to lack of proper monitoring. Bangura gas plant was shut down for lacking proper monitoring [3-5] and the Bibiyana gas plant was shut down to repair a leaking gasket. Large gas processing plant consists of thousands of measurements, hundreds or thousands of controllers and many recycle streams. To reduce the frequency and consequences of accidents of chemical process operation, classical methods for fault detection are implemented. However, classical methods for fault detection in industries depend on human supervision and expertise. Again, operator of modern plant is saturated by alarm of supervisory control and data acquisition (SCADA) and Distributed control system (DCS) and difficult to manage the multiple fault simultaneously. Therefore, the above incidents clearly show the necessity of pro-active real time techniques for fault detection. A number of real-time monitoring techniques for chemical and petrochemical processes, such as extended kalman filter, signed diagraph, qualitative simulation, statistical method and neural network has been suggested in literature [6-12]. The use Neural Networks (NNs), in all aspects of process engineering activities, such as modeling, design, optimization and fault diagnosis, error detection, data reconciliation etc. has been considerably increased in recent years [8,11,12]. To the best of our knowledge, there has been no work reported in literature on using NN based fault detection system for gas processing plants in Bangladesh.

In this work, the steady state model of Brahmanbaria gas processing plant is developed using Aspen HYSYS and is validated using real plant data. Then, the dynamic model of the plant is developed from steady state model to understand the real plant behaviour and plant disturbances. Finally, an attempt has been made to study the fault detection of Brahmanbaria gas processing plant using NN based system. Early malfunction of liquid control valve in the plant is distinguished by using NN based Fault detection system from various parameters.

II. Brahmanbaria Gas Process Plant

Aspen HYSYS is user friendly software for simulation of chemical plants and oil refineries [13]. In this process (Fig.1) gas steam from air cooler flows through two phase vertical separator where, liquid separates from the gas. The overhead product gas passing through gas-gas exchanger, the gas goes to another two phase vertical separator where the bottom liquid product goes to liquid storage tank preheated by steam heater. The heavier hydrocarbon collected in the liquid storage tank is pumped to a distillation column with twenty trays.

III. Neural Network Fault Detection Scheme

Any non-linear relationship between input and output of a system can be captured effectively using NNs. NNs are consist of a large number of primitive computational elements called neuron. NN based fault detection are based on classification of historic process knowledge. The development of the NN based system involves selecting suitable architecture to differentiate between the fault of the process with the normal condition. The steps of NN based fault detection system in this work is shown in Fig. 2 and Fig. 3. NN is trained, validated and tested are similar to stated as [10] is shown in Fig. 4 and Fig. 5. Historic data of 10 key variables which affects the different mode of operations (types of faults and normal) is fed to the input layer and mode of operations fed to the output layer of the NN. NN is trained, validated and tested using dynamic data. Several multi layered feedforward neural networks with varying configurations and Levenberg Marquardt back propagation algorithm are also employed in the training and testing process of the to obtain optimum neural network architecture.

[*] Part of the work is presented at 62nd Canadian Chemical Engineering Conference

978-1-4799-4166-7/14/$31.00 ©2014 IEEE

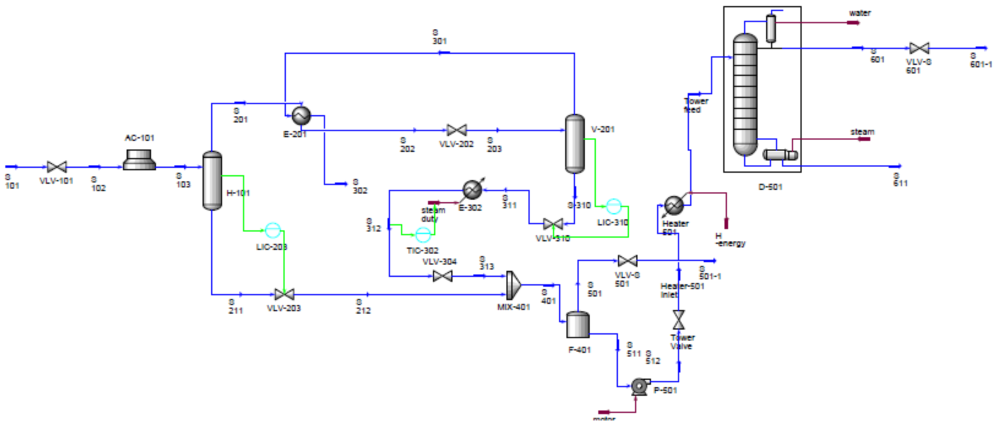

Fig. 1 Process Flow Diagram the Brahmanbaria Gas processing Plant.

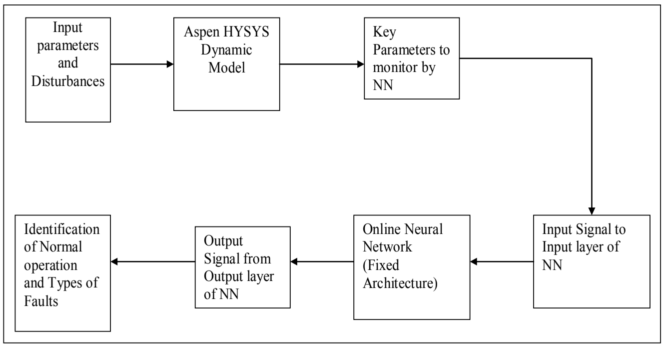

Fig. 2 NN based fault detection system

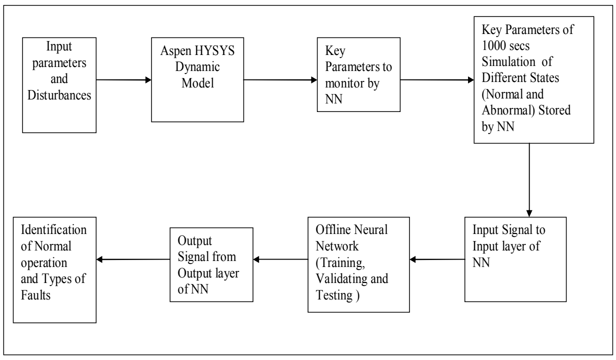

Fig. 3 Offline NN based fault detection

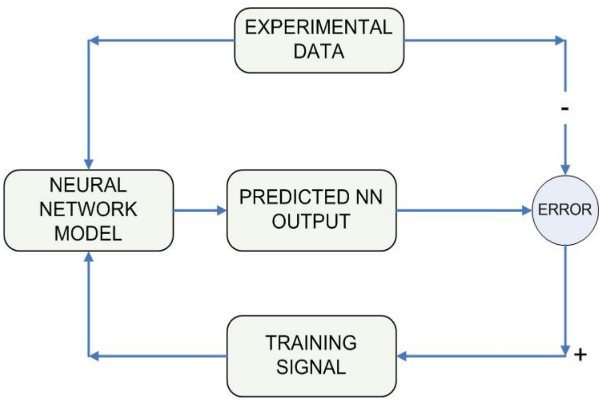

Fig. 4 Neural Network Backpropagation Training Scheme.

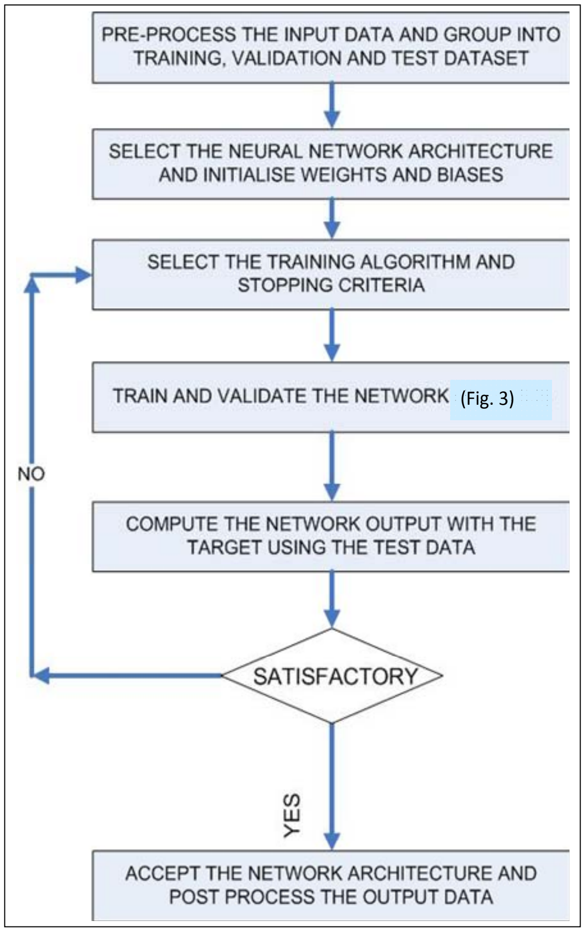

Fig. 5 The steps of NN model development.

IV. Results And Discussion

Table I shows the design specification of the Brahmanbaria Gas processing Plant Model (Fig. 1) within Aspen HYSYS. 1700 sample data for key parameters from the normal situation to each type of faults are simulated using Aspen HYSYS simulator. The key data (Table III) of different normal operation mode using Aspen HYSYS simulator are shown in chart forms from Fig. 6 and sample fault (Table II) in the process plant generated using dynamic model are shown in chart forms from Fig. .7. However, visually distinguished such data pattern is quite difficult.

Those data for each key parameters are monitored by NN based fault detection system and fed to neural network input layer (Table III). Types of Operation Mode/Disturbance Criteria (Table II) is integrated with Output layer Neuron of NN based system. Neuron of output layer for each states value equal to 1 and for absent of the states value equal to 0 (Table IV). Data sets are sorted to avoid uneven distribution. All data are scaled to the symmetrical range of -1 to +l.

TABLE I
INPUT-OUTPUT PARAMETER

Stream Name	**S 101**	**S 302**	**Heater-501 Inlet**
Temperature (°F)	150	98	62
Pressure (psia)	3000	1024	19
Mass flow (lb/hr)	57112	39789	11314
Stream Name	**Tower feed**	**S 601**	**S 611**
Temperature (°F)	62	14	350
Pressure (psia)	19	14	16
Mass flow (lb/hr)	11314	10113	1201

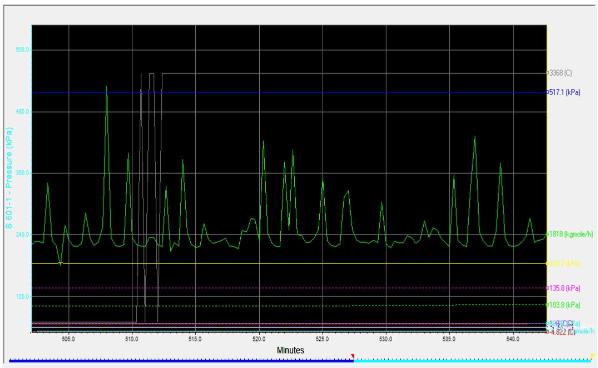

Fig. 6 Normal operation mode by HYSYS

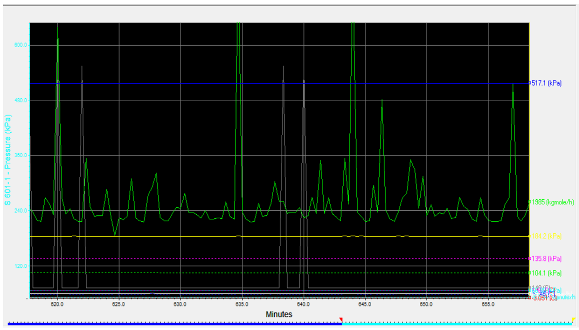

Fig. 7 Tower valve disturbance HYSYS model

TABLE II
DIFFERENT PARAMETERS MONITOR BY NN TO IDENTIFY OPERATION STATES

Different Parameters and Different Layer Neuron			
Monitor Variables and Input layer Neuron of NN	Tower feed Molar Flow	Tower feed Temperature	Tower feed - Pressure
	S 601-1 - Molar Flow	S 601-1 - Temperature	S 601-1 - Pressure
	S 611-1 - Molar Flow	S 611-1 - Temperature	S 611-1 - Pressure
	S 302 - Molar Flow		S 302 - Pressure
	S 401 - Molar Flow	S 401 - Temperature	S 401 - Pressure

TABLE III
TYPES OF OPERATION MODE/DISTURBANCE CRITERIA

Different states (normal and abnormal) and Output layer Neuron	**Operation Mode/Disturbance Criteria**		
	Normal operation	Tower valve open	Tower valve close
		VLV-203 & 304 open	VLV-203 & 304 close

TABLE IV
NN ARCHITECTURE FOR DIFFERENT CONDITIONS

Condition	**Normal**	**Abnormal**			
		Tower valve open	**Tower valve close**	**VLV-203 & 304 open**	**VLV-203 & 304 close**
NN output layer	$\begin{bmatrix}1\\0\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0\\1\\0\\0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\1\\0\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\0\\1\\0\end{bmatrix}$	$\begin{bmatrix}0\\0\\0\\0\\1\end{bmatrix}$

Training of NN Fault detection system is shown in Fig. 8. The statistical regression plots of (Fig. 9 to Fig. 10) between predicted and target data of different operation mode are plotted. Network architecture is updated until the regression value is almost close to 1. Optimum network is found for this work with 9 neurons in hidden layer.

However, If the setpoint of normal operation is changed whose response is not similar to the training pattern network, NN fault detection might detect as normal operation. Hyperbolic tangent functions are used in the input and hidden nodes. Linear functions are used in the hidden layer and output nodes.

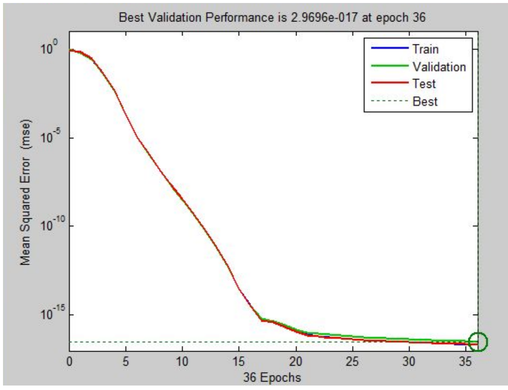

Fig. 8 Training of NN Fault detection system

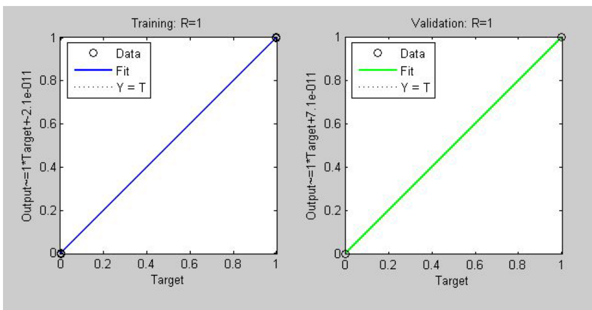

Fig. 9 Regression analysis of NN predicted data with Fault

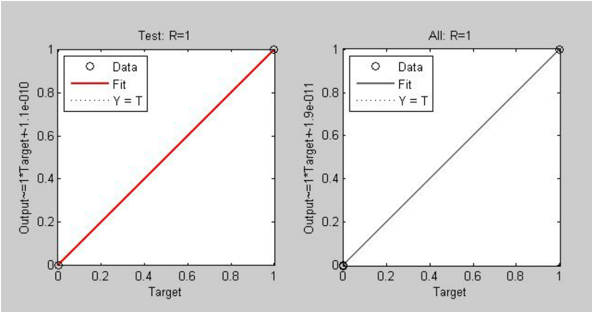

Fig. 10 Regression analysis of NN predicted data with Fault

Predictions by optimum NN within the training range follow the expected trends and it is within the engineering accuracy (Fig. 11 and Table V). This probe that optimum network able to predict types of fault (here liquid control valve failure for product quality loses) even when the network is with new inputs (test data).

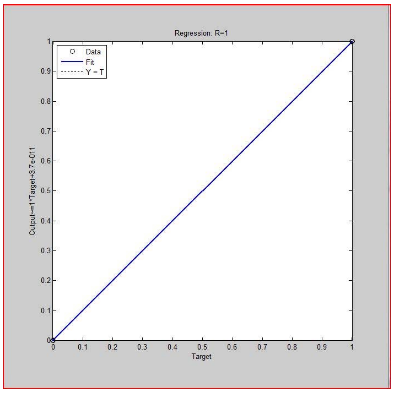

Fig. 11 Regression analysis of NN predicted test data

V. Conclusions

The priority of fault detection is increasing. Brahmanbaria Gas Plant behaviour and disturbances are studied using HYSYS dynamic model. Disturbance data are shown in chart form. A feedforward NN based fault detection was developed to identify the fault (disturbance) and no fault (normal) in plant operation. The NN based fault detection system was be trained, validated and tested using the dynamic model data. preliminary results show that NN based fault detection able to identify realistic fault output.

Authors believe that, NN based fault detection will help to avoid accident events and productivity losses in Gas processing industry in Bangladesh and help operators to identify and monitor multiple fault in real-time.

Acknowledgment

We express our gratitude to the Professor I.M.Mujtaba, University of Bradford, UK in neural networks whose his support has been a inspiration to us.

References

[1] M. Rahman, and M. Tamim, and L. Rahman "Analysis of natural gas consumption by industrial sector of Bangladesh," *Journal of Chemical Engineering*, *IEB*, vol. 27, pp. 1–7, June 2012.

[2] M.T. Sowgath, Z. M Hossain, and S. Kawsher, "Maximising the Heat Content of Sales Gas at Kailashtilla Gas Processing Plant " *Chemical Engineering Transactions*, vol. 24, pp. 313-316, 2011.

[3] (2013) The daily-sun website. [Online]. Available: http://www.dailysun. com/ access at July 10 2014./

[4] (2008) The daily-sun website. [Online]. Available: http://www.thedailystar.net/newDesign/news-det / access at July 10 2012./

[5] (2008) The Financial Express. [Online]. Available: http:// http://www.thefinancialexpress-bd.com/2008/0/ access at July 10 2012./

[6] D. M. Himmelblau, *Fault Detection and Diagnosis in Chemical and Petrochemical Processes*, Elsevier Scientific Publishing Company, Amsterdam, Oxford, New York, 1978.

[7] D. M. Himmelblau and M. A. Hussain, "Fault Detection and Diagnosis in Chemical and Petrochemical Processes", Vol-8 Berlin, Amsterdam: Elsevier Scientific Publishing Company, 1978.

[8] I. M. Mujtaba and M. A. Hussain, Ed., *Neural Networks and Other Learning Technologies in Process Engineering*, London, Imperial College Press, 2004, Vol. 3.

[9] M.T.,Hagan H.B. Demuth and M.N. Beale, *Neural Network Design*,: 1st edition PWS Publishing Company of International Thomson Publishing Inc, 1996.

[10] M.S. Tanvir and I.M., Mujtaba Neural network based correlations for estimating temperature elevation for seawater in MSF desalination process, Elsevier, 2005, 195, 251-72.

[11] Y. Maki, and K. A. Loparo, "A Neural Network Approach to Fault detection and Diagnosis in Industrial Process," *IEEE Transaction on Control Systems technology*, vol. 5, No. 6 pp. 529–541, Nov. 1997.

[12] V. Venkatasubramanian, R. Rengaswamy, S. N. Kavuri, and K. Yin, "A Review of process fault detection and diagnosis Part III: Process history based methods," *Computers and Chemical Engineering*, vol. 27, pp. 327-346, 2003.

[13] HYSYS, HYSYS 3.2 user guide, Hyprotech Ltd, http://www.hyprotech.com/

TABLE V
SAMPLE FAULT SCHEME RESULT FOR TEST DATA

	Tower feed Temperature	S 601-1 - Pressure	Tower feed Pressure	S 601-1 - Temperature	S 611-1 - Temperature	S 611-1 - Pressure	S 302 - Molar Flow	S 302 - Pressure	S 401 - Temperature	S 401 - Pressure	Output Neuron Value					Output Neuron Value by NN				
	[F]	[psia]	[psia]	[F]	[F]	[psia]	[MMSCFD]	[psia]	[F]	[psia]	1	0	0	0	0	1	4.03374E-09	-9.98884E-10	-5.25759E-10	-2.23052E-09
Normal Operation	121	10	19	214	225	20	24	75	101	10	1	0	0	0	0	1	4.87022E-09	-1.01484E-09	-1.02606E-09	-2.48704E-09
	121	10	19	214	225	20	24	75	104	10	1	0	0	0	0	1	8.74083E-10	3.62786E-10	-3.46233E-10	-5.62695E-10
	119	10	17	188	225	20	25	75	104	10	1	0	0	0	0	1.000000003	6.49216E-09	-2.05814E-09	6.919E-10	-7.83192E-09
	119	10	17	188	225	20	24	75	99	10	1	0	0	0	0	0.999999994	5.27751E-09	3.90782E-09	-1.00769E-09	-2.55304E-09
Tower valve full open fault	79	14	191	10	225	20	24	75	10	68	0	1	0	0	0	3.80625E-10	1.000000001	2.16216E-09	4.48077E-10	-4.317E-09
	79	14	191	10	225	20	23	75	10	68	0	1	0	0	0	5.33552E-10	0.999999986	2.48718E-09	-4.40562E-10	1.15456E-08
	79	14	191	10	225	20	25	75	10	68	0	1	0	0	0	2.36126E-10	1.000000014	1.75591E-09	1.50443E-09	-1.78391E-08
	76	12	155	10	296	20	24	75	10	68	0	1	0	0	0	8.636E-11	1.000000003	-1.92406E-10	-2.2108E-09	-8.29511E-10
	76	12	155	10	296	20	24	75	10	68	0	1	0	0	0	1.00077E-10	1.000000003	-2.23888E-10	-1.98415E-09	-5.09009E-10
Tower valve full close fault	180	7	-76	10	225	20	24	75	10	68										
											0	0	1	0	0	3.22709E-09	-3.89884E-09	1.000000001	-1.69263E-09	1.03893E-09
	179	7	-76	10	225	20	24	75	10	68	0	0	1	0	0	3.15343E-09	-4.48098E-09	1.000000001	-1.78324E-09	2.20213E-09
	178	7	-76	10	225	20	24	75	10	68	0	0	1	0	0	3.79229E-09	-5.05028E-09	1.000000003	-1.91119E-09	2.02801E-10
VLV-203&304 full open fault	373	25	81	10	260	20	24	75	69	374										
											0	0	0	1	0	3.5087E-10	2.13279E-10	1.59257E-10	0.999999999	9.77164E-11
	373	25	81	10	260	20	24	75	69	374	0	0	0	1	0	6.38787E-10	-1.54718E-10	-1.23796E-10	1	-5.15153E-11
	373	25	81	10	260	20	24	75	69	374	0	0	0	1	0	2.169E-10	-7.39016E-10	-7.82877E-10	1	1.06334E-09
VLV-203&3	150	18	216	10	225	20	24	75	10	166	0	0	0	0	1	2.84952E-10	1.39294E-08	1.93263E-11	-1.36459E-08	0.999999999
	150	18	216	10	225	20	23	75	10	166	0	0	0	0	1	4.5815E-10	2.62054E-08	3.29405E-10	-1.66684E-08	0.99999999
	149	18	218	10	225	20	24	75	10	93	0	0	0	0	1	-4.74787E-12	-2.54849E-09	1.70005E-11	-2.0985E-10	1.000000003
	149	18	218	10	225	20	24	75	10	93	0	0	0	0	1	-1.26436E-11	-3.24281E-09	3.33034E-12	-9.03236E-11	1.000000003