4.1 DNR-TCOON: AN INTEGRATED OBSERVATION AND OPERATIONAL FORECAST SYSTEM FOR THE GULF OF MEXICO

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1. Introduction

The Gulf of Mexico (GOM) is of primary importance to both the United States (US) and Mexico. More then half of the waterborne US tonnage transits through its waterways, 93% of the US offshore oil production and about 98% percent of the Natural gas production come from its waters, USACE (2001). The population along its shorelines has been steadily increasing, totaling 46.7 million in 1999 for the US portion of the GOM, while the population along its tributaries and the Mississippi river in particular has been increasing as well. Anthropogenic impacts are an associated and growing concern as for example the GOM has the largest zone of human caused coastal hypoxia in the Western Hemisphere. To preserve the health of the GOM while accommodating growing human activities will require a dedicated and informed multinational stewardship. Given the size and the intricacies of the GOM ecosystem an essential component of a good decision making process will be the availability of extensive and consistent coastal, ocean and riverine observations and models. Such systems are being steadily developed and improved; the network of stations managed by the Texas A&M University-Corpus Christi Division of Nearshore Research (DNR) is one of the largest and most sophisticated in the Gulf of Mexico. The following sections present a brief description of the DNR network, Michaud (2001), its capabilities, funding and user base, and its unique software and procedures. The second part of the article discusses models including a set of growing Artificial Intelligence (AI) based models that take advantage of the large amount of real-time information to compute short term operational forecasts.

2. DNR-TCOON NETWORK

The network started with the installation in 1989 of a system to provide real-time water-level and meteorological information to the City of Corpus Christi to assist local officials with preparations for incoming hurricanes and tropical storms. The network has grown steadily and at present DNR manages 53 active monitoring platforms along the Texas coast. The stations include the 29 platforms of the Texas Coastal Ocean Observation Network (TCOON), the 7 water level monitoring platforms of the National Ocean Service National Water Level Observation Network in Texas. The primary goal of this group of stations is to establish and maintain tidal datums. The operation of these stations is funded by a growing group of state and federal entities including the Texas General Land Office, the Texas Water Development Board, the National Oceanic and Atmospheric Administration (NOAA) and the US Army Corps of Engineer. Through the sharing of their resources the stakeholders benefit from a more extensive and sophisticated network. This sharing of resources is an important advantage for the long term stability and management of a coastal observation network in times of growing budgetary constrains. Decision making and overall priorities are discussed during yearly meetings including the stakeholders and DNR staff. The other monitoring stations of the network are funded by and maintained for other local entities. They include a real-time navigation system to provide real time accurate water level, current and wind speed and direction for safe navigation to and from the Port of Corpus Christi, the 6th largest port by tonnage in the US. Pilots and port officials can access the data by phone or through the World Wide Web and receive up to the minute readings of conditions at several stations along the Corpus Christi Ship Channel. Another set of 5 stations monitors salinity in Nueces Bay, Texas and helps manage freshwater releases from the upstream dams along the Nueces River. The location of the majority of these stations is illustrated in Figure 1.

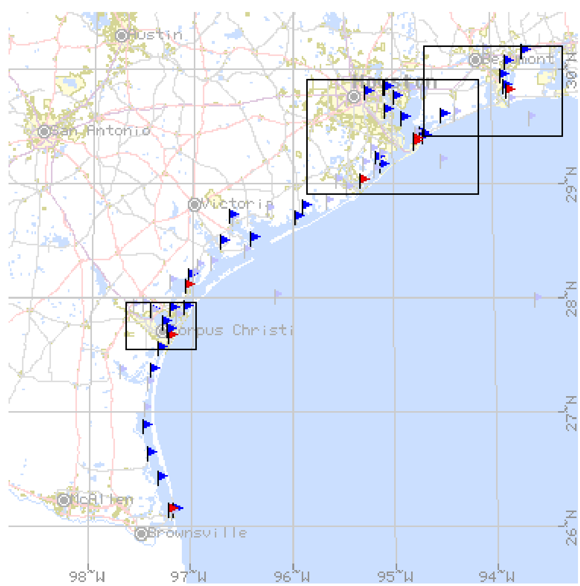

Figure 1. Location along the Texas coast of the TCOON stations and other active stations managed by TAMUCC DNR.

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The overall combination of these stations provides real-time or near real-time coastal measurements for the Texas Gulf coast generating the following time series: water levels, wind speeds, wind directions, barometric pressures, dissolved oxygen, salinity, water currents and wave climates depending on the station. While the primary use of the data has been to establish tidal datums and literal boundary definitions, present users include recreational boaters, sailors, windsurfers, the shrimp and fishing industry, marine construction, operators of channel dredging and maintenance as well as decision-makers responsible for marine safety, oil spill response and emergency evacuation in the event of an approaching hurricane.

DNR is also assisting a group of Mexican scientists from the Instituto Politecnico Nacional (IPN) and the Universidad Nacional Autonoma de Mexico (UNAM) to develop a water level monitoring network similar to TCOON along the Mexican Gulf coast called Red de Observaciones y Predictiones de Variables de Oceanicas (ROPVO). The DNR and ROPVO networks are part of a growing list of coastal and Ocean Monitoring networks in the Gulf of Mexico. The networks include the Louisiana State University Coastal Studies Institute Stations, WAVCIS, (2004), the Louisiana University Marine Consortium, LUMCON (2004), the National Data Buoy Center, NDBC (2004), the Texas Automated Buoy System, Kelly (1998), the University of Southern Florida's Coastal Ocean Monitoring and Prediction System, COMPS (2004). Standards are also being developed and implemented to facilitate the sharing of data between observation networks. Examples include OPeNDAP (2004) which is a framework that aims at simplifying all aspects of scientific data networking. Other related efforts include the National Virtual Ocean Data System or NVODS (2004) which is a framework for the distribution and analysis of oceanographic (and other) data from researchers and other data providers to intermediate and end users.

3. DNR AUTOMATED DATA MANAGEMENT

A distinctive feature of the DNR network is its unique data management software which provides data in real-time or near real-time to its sponsors and the community through the World Wide Web and through automated phone services. The software and procedures were developed on the principle that all user interaction with the data management system takes place via web-based interfaces, Michaud (2001). Such interactions include for example site visit and maintenance reports and chain-of-custody records. Sponsors, scientists and other potential users can access all DNR data in a variety of graphic and text-based formats from **http://lighthouse.tamucc.edu/**. The DNR software and hardware were built and combined with a primary goal of reliability. The data are housed in ordinary PC-base computers rather than sophisticated proprietary systems such that parts or whole systems can be replaced quickly if needed. The software is based on open source technologies such as Linux and Perl such that DNR is not subject to changes in proprietary systems and has the flexibility to replace software components as new technologies become available or as the needs of DNR's sponsors evolve. DNR has started providing access to all its software under the General Public License and aims at co-developing future versions of the web-based software and procedures.

4. DATA INTENSIVE AUTOMATED FORECASTS

The growing availability of both real-time data and extensive and consistent environmental time series allows for new modeling techniques. DNR has been taking advantage of these real-time data streams to develop data intensive prediction models, statistical model, neural network models and rule based models. When the time series encompass most encountered conditions such models can be trained to quantify relationships between past observations and future outcomes. For cases such as point/local forecasts these models can have significant advantages over other models such as classic statistical models and Finite Element/Finite Differences models. These advantages include the ability to model non-linear relationships and the implicit inclusion of the boundary conditions and forcing functions. Also once the models are trained AI based predictions are computed virtually instantly. DNR has implemented as part of its overall software the ability to store model parameters and compute model outputs on demand. Examples include a tool to compute tidal constituents based on past water level time series and output the related harmonic forecasts based on the computed constituents or constituents obtained otherwise, Mostella (2002).

Based on harmonic forecasts and real time water level measurements persistence model forecasts for water levels were enabled on the DNR website in the spring of 2003. Developing improved water level forecasts techniques for the coast of Texas is important as tidal forecasts do not meet NOAA standards for the overall Texas coast, Tissot (2004). Persistence water level forecasts are based on the assumption that the difference between the present measured water level and the level predicted by harmonic forecasts will stay constant. While conceptually simple this model takes advantage of the real time data of the network and produces automated 48-hour water level forecasts updated every hour. The predictions have been used by coastal users and in particular by coastal emergency managements and the National Weather Service during the approach of storms such as 2003 hurricane Claudette. While by their nature persistence model forecasts are inaccurate, lagging water level changes due to atmospheric inputs, these shortcomings are predictable. Given the inertial nature of water levels persistence model forecasts are increasingly accurate for shorter term forecasts and are a very useful and complementary tool to longer term forecasts issued during the approach of tropical storm and hurricanes by NOAA. Figure 2 presents a display from the DNR website of water level predictions issued during the passage in the Gulf of Mexico of Hurricane Ivan for the

Bob Hall Pier Station located near Corpus Christi, Texas. While the storm's impact was considerable in the eastern portion of the Gulf of Mexico water levels were also affected on the Texas Gulf Coast leading to beach closures and beach erosion. Persistence model performance for 12-hr, 24-hr and 48-hr forecasts can be consulted online for the 5 days. An example of the model performance for 12-hr predictions is displayed in figure 3 for the Port Aransas Station while impacted by hurricane Ivan. While the water levels were up to more than 1 foot above tidal levels 12 hour persistence forecasts were always within 0.2 feet of the measurements. The persistence model forecasts are also compared to harmonic forecasts and measurements in the web displays.

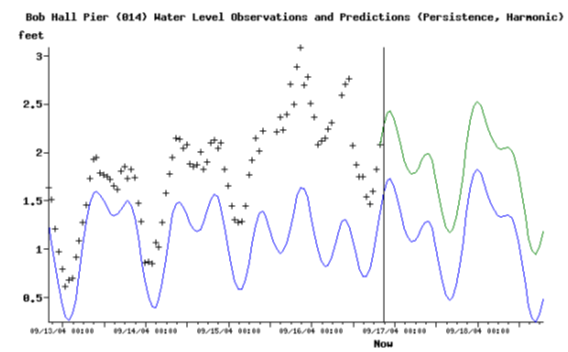

Figure 2. DNR Website display of persistence model predictions of water levels for Bob Hall Pier, Texas during the passage of 2004 hurricane Ivan in the Gulf of Mexico. The black crosses are past measurements, the blue line represents harmonic forecasts and the green line persistent model forecast.

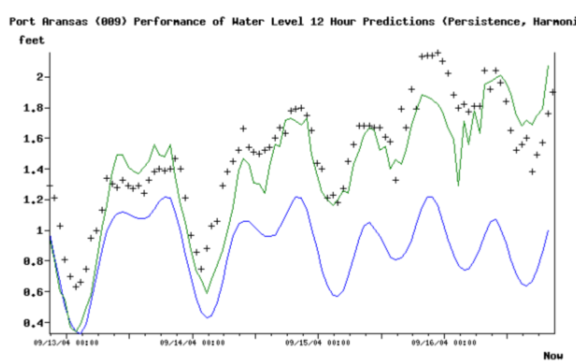

Figure 3. DNR Website display of the performance of the persistence model for 12-hr forecasts at Port Aransas, Texas during the passage of 2004 hurricane Ivan in the Gulf of Mexico. Lines and crosses are same as Figure 2.

As the difference between measured and harmonically forecasted water levels is correlated with atmospheric conditions and in particular wind speeds and wind directions, Garvine (1985) and Cox (2002), other models have been developed to forecast water levels including statistical models and Artificial Neural Network (ANN) models, Tissot (2004). ANN models in particular can capture the non linear relationship between wind forcing and future water level changes and in general are well suited to take advantage of the extensive availability of real time measurements to model environmental systems. A typical schematic of a neural network as applied to the prediction of water level changes is presented in figure 4. Further description of the training and optimization of ANN models for water level forecasts is presented in Tissot (2002, 2003) and the comparative performance of ANN models and other models for water level predictions for Texas Ports and Waterways is discussed in Tissot (2004).

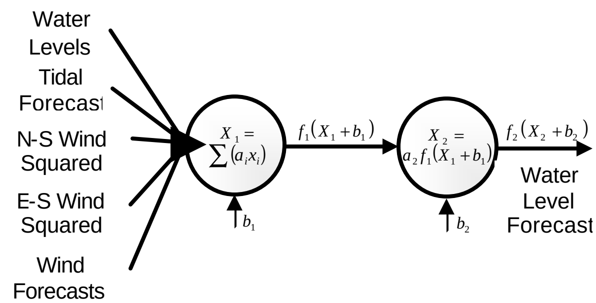

Figure 4. Schematic of the type of Neural Network Model used by DNR to predict water levels.

As adding wind measurements as part of the ANN model inputs improves the accuracy of water level predictions DNR and the Corpus Christi Weather Forecasting Office (CCWFO) have been collaborating to develop databases of historical atmospheric forecasts from the National Center for Environmental Predictions (NCEP) Eta-12 and GFS models, Patrick (2002). These time series of past atmospheric predictions include wind predictions and have been recently made available on the DNR website, DNR (2004). New ANN models are presently being developed to take advantage of wind forecasts. A schematic of the operation of the upcoming ANN based forecasting system based on wind forecasts and coastal measurements is presented in figure 5. As wind forecasts are relatively similar to the corresponding wind measurements for DNR stations, Stearns (2002), the performance of ANN models including wind forecasts can be estimated by replacing wind forecasts by wind measurements. The performance of the different models can be evaluated by using the National Ocean Service skill assessment statistics listed in Table 1, NOAA (1999). Tables 2 to 4 present compare model performance for one station on the open coast, Bob Hall Pier and 2 stations located inside embayments, Rockport and Packery Channel all located near Corpus Christi, Texas. The models compared are harmonic forecasts, persistent model forecasts (pers), ANN without wind forecasts (NN-1) and ANN with wind forecasts (NN-2). The ANN models are trained over a 1-year data set and the performance of all models is evaluated based on 3 years of hourly data from January 1st 2000 to December 31st 2002.

Table 1. NOS skill assessment statistics for water level predictions, NOAA (1999).

Average error: $E_{avg} = (1/N)\ \Sigma\ e_i$

Root Mean Square Error: $E_{rms} = ((1/N)\ \Sigma\ e_i^2)^{1/2}$

POF(X) – Positive Outlier Frequency or percentage of the forecasts X cm or more above the actual measurement

NOF(X) – Negative Outlier Frequency or percentage of the forecasts X cm or more below the actual measurement

MDPO(X) – Maximum Duration of Positive Outlier

MDNO(X) – Maximum Duration of Negative Outlier

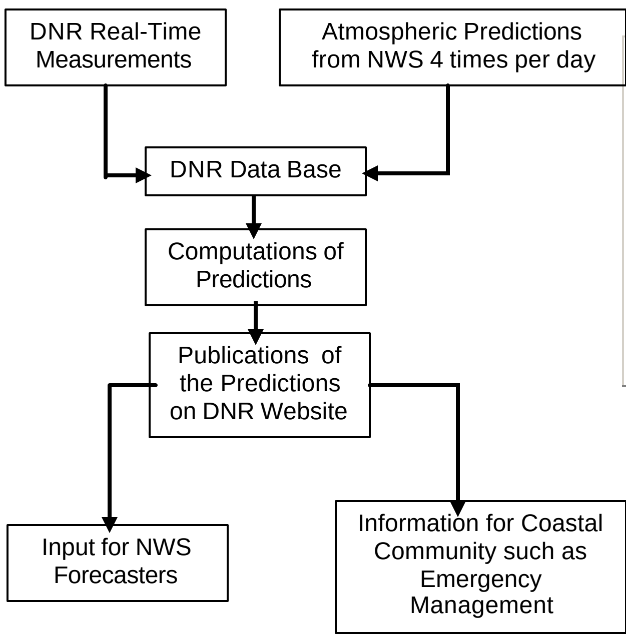

Figure 5. Schematic of information flow from measurements and atmospheric predictions to web publication for ANNs forecasting water levels based on coastal measurements and atmospheric forecasts.

Table 2. Average model performance comparison for Bob Hall Pier, Texas - open coast – 2000-2002.

Model	RMSE m	CF %	POF %	NOF %	MDPO hrs	MDNO hrs
Harmonic	0.122	82.71	0.29	2.59	12	48
Pers. 24-hr	0.091	91.16	0.55	0.38	11	12
NN-1 24-hr	0.086	92.61	0.18	0.46	9	17
NN-2 24-hr	0.081	93.87	0.14	0.34	6	14
Pers. 48-hr	0.121	82.46	1.56	1.00	30	23
NN-1 48-hr	0.110	85.79	0.56	1.24	18	28
NN-2 48-hr	0.097	89.13	0.28	0.63	12	17

Table 3. Average model performance comparison for Rockport, Texas – embayment - 2000-2002.

Model	RMSE m	CF %	POF %	NOF %	MDPO hrs	MDNO hrs
Harmonic	0.11	85.02	0.21	1.90	16	73
Pers. 24-hr	0.069	95.75	0.25	0.02	14	0.6
NN-1 24-hr	0.059	97.85	0.13	0.10	8.5	7.6
NN-2 24-hr	0.053	98.56	0.12	0.08	8.4	6.2
Pers. 48-hr	0.101	87.18	0.78	0.42	25.4	13.8
NN-1 48-hr	0.089	91.40	0.120	0.57	9.6	26.4
NN-2 48-hr	0.078	94.50	0.12	0.30	6.8	16.3

Table 4. Average model performance comparison for Packery Channel Texas – embayment- 2000-2002.

Model	RMSE m	CF %	POF %	NOF %	MDPO hrs	MDNO hrs
Harmonic	0.105	87.87	0.02	1.99	1	106
Pers. 24-hr	0.061	96.69	0.14	0.06	7	3
NN-1 24-hr	0.054	97.96	0.03	0.17	2	14
NN-2 24-hr	0.050	98.60	0.03	0.14	2	11
Pers. 48-hr	0.087	91.82	0.53	0.51	23	19
NN-1 48-hr	0.078	94.24	0.09	0.58	4	25
NN-2 48-hr	0.068	96.38	0.07	0.29	4	16

As can be seen in the above tables the harmonic forecasts or tide tables performance is consistently below the Central Frequency of 90% required by the National Ocean Service for operational models, NOAA (1999). Both the persistence model and the ANN models greatly improve upon harmonic forecasts and have all Central Frequencies above 90% for 24-hour forecasts. A comparison of water level measurements and 24 hour forecasts is presented in Figure 6 for 1998 and the Rockport, Texas Station. The small tidal range as compared to the measured water level variation is evident from the figure as well as the relatively good performance of both the persistence and the ANN models. Note the performance of the models around day 250 during the passage of tropical storm Frances which lead to flooding of coastal areas. Figure 7 presents a similar comparison for 24 hour water level forecasts on the open coast at the Bob Hall Pier station. Both ANN forecasts for figures 6 and 7 are computed without wind forecasts. For 48 hour forecasts ANN models with and without wind forecasts have Central Frequencies above 90%. The wind forecasts lead to two to three percentage point improvements. None of the models passed the 90% central frequency test for 48 hour forecasts on the open coast although the ANN model with wind forecasts had a CF of 89.1%. The better performance of the models within embayments is not surprising as the behavior of water levels within Texas bays and estuaries is mostly driven by the Gulf of Mexico and ANN embayment models include input from stations on the open coast. Water level changes in the embayments are also dampened by the narrow passes with the Gulf of Mexico leading to dampened changes in water levels during storms and better performance for the ANN models as well as the persistence model. The performance of the persistence model during major storms has been discussed before.

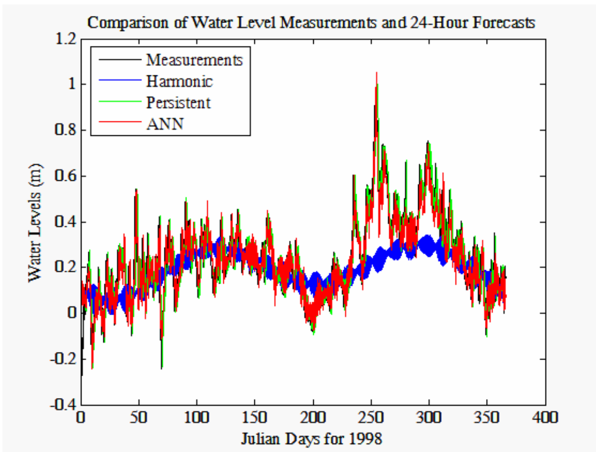

Figure 6. Comparison of water level measurements and 24 hour water levels forecasted by the harmonic, persistent and ANN models for 1998 at the Rockport, Texas Station (embayment).

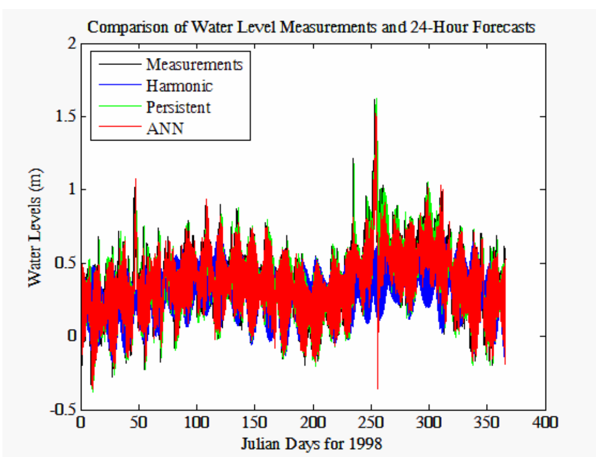

Figure 7. Comparison of water level measurements and 24 hour water levels forecasted by the harmonic, persistent and ANN models for 1998 at the Bob Hall Pier, Texas, Station (open coast).

The performance of ANN models during storms is presently studied. An example of the comparative performance of the models during the passage of hurricane Brett is presented for the Rockport station in Figure 8. Brett made landfall near Port Mansfield, Texas about 80 miles south of Rockport. The 12 hour ANN forecasts predict water levels up to 15 cm above the measured levels while the persistence model under predicts by about 10 cm during the initial storm phase. The accuracy of water level predictions during storms varies significantly with forecast time and location with best performance achieved for short forecast times and embayment locations. Guidelines for the use of both ANN and persistence models during storms are under development. One of the difficulties of predicting water levels during storms using ANNs is that large storms often have unique features and dynamic. As the overall number of storms on records for DNR-TCOON is still relatively small the evaluation and specific storm training of the models is more difficult then for regular conditions and frontal passages. Nevertheless the technique is promising and the models performance during storms is expected to improve as the database of storm passages becomes more substantial and specific ANN modeling techniques are developed.

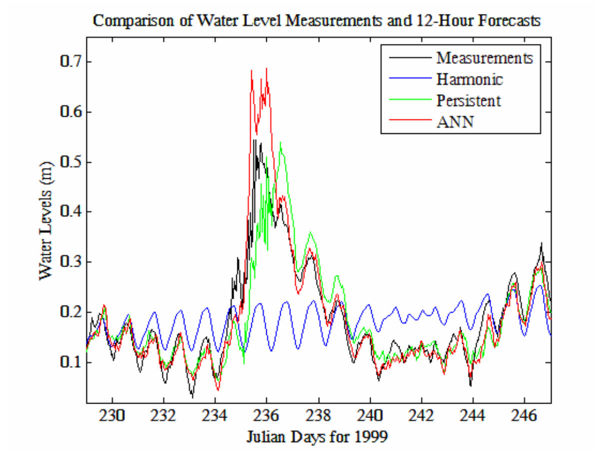

Figure 8. Comparison of water level measurements and 12 hour water levels forecasted by the harmonic, persistent and ANN models during the passage of 1999 hurricane Brett at the Rockport, Texas Station.

Other models under development include a model to predict indicator bacteria counts in coastal recreational waters based on precipitation, riverine flows and other coastal measurements such as air and water temperatures, Cook (2004), models to forecast spring flows and water levels in a karst aquifer Lalmansingh, (2004), and models for cross station nowcasting within embayment systems in the event of station malfunctions, Durasaimy (2004). Other tools which have been developed to take advantage of the computational infrastructure of the DNR network include gap filling, Mostella (2004) and spike detection algorithms, Rush (2004). These tools provide researchers with the option to fill minor gaps in time series and work with the continuous data sets often required for data intensive type models.

5. CONCLUSION

The increasing availability of a wide range of real-time data is making possible the development and implementation of new data intensive modeling techniques for the coastal zone. Once established/trained these models are computationally very efficient and can provide real-time predictions on the World Wide Web or other communication systems. These models are increasingly helping coastal management personnel in their decision making process as well as providing a wide range of information and predictions for the coastal communities at large. Models recently implemented at TAMUCC-DNR are used for safer navigation in the Texas waterways, during storm approaches and by a number of recreational users. The range of such applications should continue to increase with the growing availability of real-time coastal measurements and the decrease in costs for computational and communication equipment.

6. ACKNOWLEGEMENTS

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