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Low-Cost MEMS-Based NARX Model for GPS-Denied Areas

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Abstract**—***Autonomous vehicle navigation has witnessed a huge revolutionary revision regarding development in Micro-Electro Mechanical System (MEMS) technology. Most recently, Strapdown Inertial Navigation System (SDINS) has successfully been integrated with Global Positioning System (GPS). However, different grades of MEMS inertial sensors are available and choosing the convenient grade is quite important. Noises in inertial sensor are mostly treated through de-noising the additive errors to improve the precision of SDINS output. Unfortunately, integration in SDINS mechanization causes a growing in SDINS error output which considered the main challenge in integrating MEMS inertial sensors with GPS. This paper aims to promote the long-term performance of the MEMS-SDINS/GPS integrated system. A new integrated structure is proposed to model the nonlinearities that exist in SDINS dynamics in addition to the error uncertainty in the inertial sensors' measurements. A robust Nonlinear AutoRegressive models with eXogenous inputs (NARX) based algorithm are designed for data fusion in the proposed GPS/INS integrated system. Validation for the proposed integrated system has been carried out using different field tests data in order to assess the accuracy of the system during GPS denied environment. The results obtained demonstrate that the proposed NARX model is applicative and satisfactory which shows a desired prediction performance.*

Index Terms**—** *INS, GPS, NARX, MEMS, IMU*

I. INTRODUCTION

Development of the first Micro-Electro-Mechanical Systems (MEMS) was presented by Draper laboratory in 1986. Since that, MEMS technology has been widely used in manufacturing. Due to ts small size, low power consumption, and cheapness, it was used in developing the inertial measurement sensors and especially accelerometers and gyroscopes. Nowadays, most of the applications like mobile robots, cameras, smart phones, platform stabilizers, most of the sport equipment's, and navigation systems are equipped with these inertial measurements unit sensors (IMU). Actually, the Inertial Navigation System (INS) is considered as one of the best common mechanical navigation devices that can afford an accurate solution for navigation based on inertial MEMS sensors. However, the minimization in size for MEMS sensors make these sensors more liable to variation in surrounding work environment like temperature, pressure, magnetic and electric fields and vibration [1].

Therefore, the accuracy of navigation solutions including position and velocity is reduced for long-term operation which depends on the grade of the MEMS sensors utilized. However, Global Positioning System (GPS) has been dominated in many equipment and vehicles. On the other hand, the researchers confront different problems in different environments where the signal of GPS is lost due to various conditions such as tall buildings and trees or inside tunnels and also degradation of signal quality during bad weather. It is clear that both navigation systems have advantages and disadvantages. Therefore, improving an inclusive navigation solution can be done through the integration between both GPS and INS systems by increasing their advantages and decreasing their disadvantages.

Kalman Filter (KF) is widely utilized to integrate both the GPS and INS systems to estimate and predict the INS error. Unfortunately, it requires a mathematical model and knowledge for the process noise covariance and sensor noise covariance matrices (Q and R matrix), and additional important

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problem for KF is the observation of altered states. Commonly, the Extended Kalman Filter (EKF) is considered as one of the most ways that used to integrate both the GPS and INS systems [2, 3].The non-linear system of EKF is linearized utilizing the first order Taylor series. However, EKF fails to produce a consistent solution during losing the GPS signal due to the neglecting the higher order terms. Moreover, different researchers [4,5] used Iterated Extended Kalman Filter (IEKF) to linearize the system model that does not overcome the estimation problem completely.

In order to provide a long-term high precise navigation solution for the moving vehicles during GPS outages, too many techniques have been proposed. Artificial Intelligence (AI) is one of the most stagnant utilized to integrate both GPS and INS systems. AI is a self-adaptive technique and very successful tool to deal with nonlinear systems. A variety of AI techniques have been used to fusion data from both GPS and INS,so that increase the accuracy of the prediction when the signal of GPS is lost. Malleswaran et al. [6] utilize Radial Basis Function (RBF) to integrate GPS with INS; however, RBF is not appropriateto implement in the real time. Moreover, Hang et al., [7] use another type of AI called Hopfield Neural Network (HNN) which also success to improve the accuracy but unlikely require a huge memory capacity to save the learning parameters.

Intelligent algorithm systems such as: Adaptive Neuro Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) have been widely utilized in different applications, especially in developing a Personal Navigation System (PNS). ANN is considered one of the most popular information processing models inspired by the nervous system of the human. Salamand Ahmed [8] utilized ANN to improve the incorporation between both INS and GPS systems through reducing the required elapsed time for learning, but unfortunately, the number of neurons in the hiddenlayer and the number of hidden layers itself was chosen by trial and error. Therefore, these drawbacks reduce the opportunity for real time implementations. Some researchers use optimization methods to determine the suitable number of hidden layers and the optimum number of nodes in each hidden layer, but, unlikely it leads to increase the complexity and time required for learning phase. On the other hand, in an unreliable environment, ANFIS is considered as one of the best solutions for system modeling, where it has the capacity to reason and learn. Many researchers [9, 10] utilized ANFIS in order to fusion GPS and INS data. However, the fuzzy system cannot learn or adapt by itself to the new environment unlike ANN. In addition to the restriction in the number of output in ANFIS structure which is limited to only one output which leads to increase the number of networks to be used in estimating more than one component for both the position and velocity.

An intelligent navigator system has been proposed to provide estimation for the vehicle dynamics. These techniques relate the raw INS data to its corresponding INS error. While [11, 12] utilized input delayed neural network in order to beat time dependency problems, since the modeling is based on the instantaneous and past raw INS data through using a dynamic sliding window. Unfortunately, this dynamic relation increases the network complexity which increases the training time.

Based on the beforehand literature, the integrated navigation systems can be classified into conventional linear systems using KF's [2, 3], non-linear systems using EKF's and intelligent techniques [13]. Currently, an intelligent technique is proposed for integrating GPS and low cost INS measurements. The proposed technique is based on nonlinear autoregressive models with exogenous inputs (NARX) model. The objective of the proposed technique is to attain an optimal integration utilizing the available information from the inertial sensors with GPS receiver and its time of availability. The layout of this paper is organized as follows: In section two, the NARX network architecture is described. The methodology of the fusing GPS/INS measurements utilizing NARX technique is illustrated in section three. The simulation results and discussion of the proposed technique are provided in section four. Finally, the concluding remarks are given in section five.

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II. NARX NETWORK ARCHITECTURE

The basic definition to the Neural Network (NN), is most properly attributed to as Artificial Neural Network (ANN), ANN is mainly processing elements (algorithms or hardware components) that are mostly trained to acquire the required knowledge in order to predict the required information during testing phase. ANN is basically consisted of different layers with a connection weights between their nodes which contain an activation function, these parameters are classified into static and dynamic as explained later.

III. STATIC NEURAL NETWORK

A neural network with the simplest and easiest structure is called a static neural network. It is an open loop network without delay or feedback connection. It allows approximating any non-stationary or nonlinear function in regular form. This neural network architectural is shown in Fig. 1, it has several layers without any feedback connections. A twisted weight *w* has associated with each connection of layers and it represents the ability of this neural structure to acquire knowledge [14].

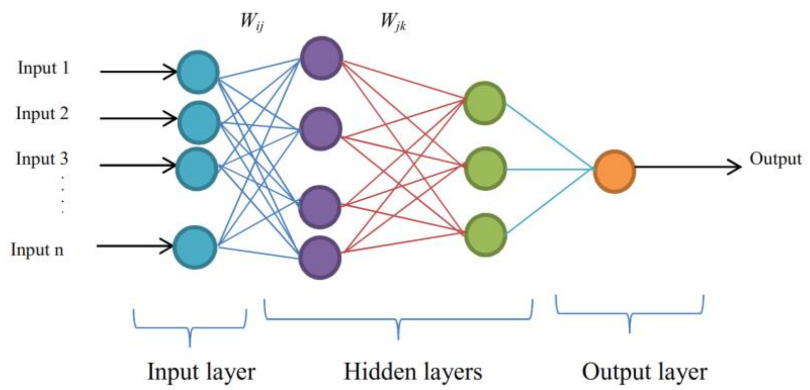

FIG. 1. THE ARCHITECTURE OF STATIC NEURAL NETWORK[14]

IV. NARX NAVIGATOR ARCHITECTURE

NARX is a nonlinear autoregressive model with exogenous inputs based algorithm designed to predict the SINS error which caused from GPS/INS integrated system. It is a fully recurrent dynamic neural network (RDNN). NARX has additional feed-back connections which surround several layers of the intended network. NARX model has two delays, one for input and one for output and it is based on Multi-layer perceptron (MLP).For nonlinear time series prediction, to get the full performances of NARX neural network using the historical values of predicted values [15].

Nowadays, NARX model is commonly used as well as compared to the other types of neural networks because this model can be used to obtain a better prediction and estimation. Also NARX model has a good feature to be used instead of the other neural networks such as a better learning, good popularization and fast convergence. In Fig. 2 NARX neural network structure can be defined depending on the discrete-time input and also output equation as represented in equation (1) [15, 16]:

$$y^P(t) = f[x(t), x(t-1), \dots, x(t-n_u), y^T(t-1), \dots, y^T(t-n_y)] + e(t) \quad (1)$$

Where $y^T(t)$ represents the desired output variable while $y^P(t)$ represents the actual output variable; $x(t)$ is the NARX neural network input variables; n_u and n_y are the input and output

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time delay variables; while $e(t)$ represents the error of the model between the desired and predicted actual output.

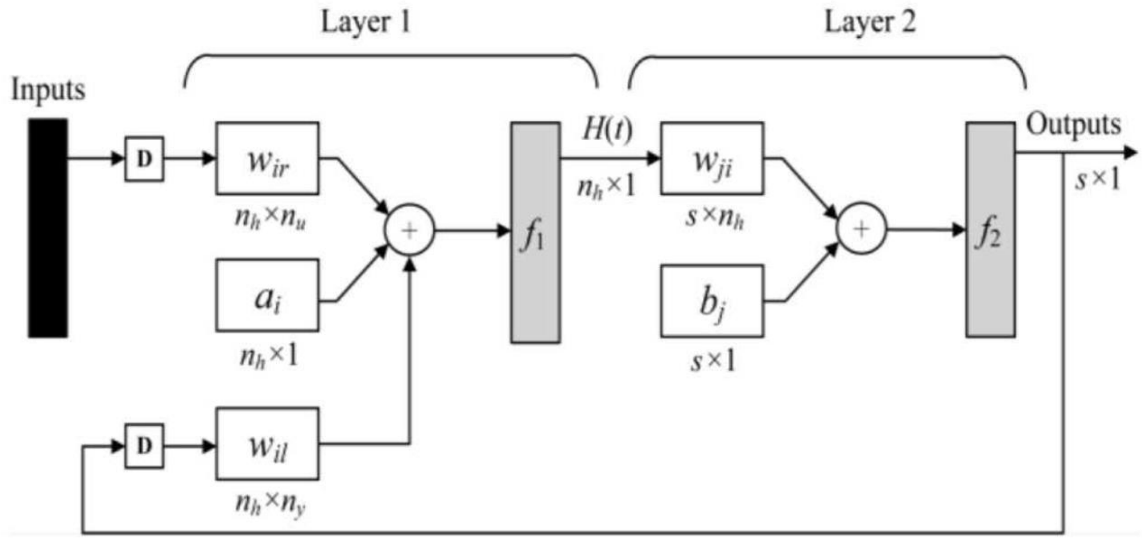

FIG. 2: NARX NETWORK STRUCTURE [15].

Through considering the input variables $x(t)$, then the value of the hidden output at specified time (t) is calculated using equation (2) as:

$$H_i(t) = f_1\left[\sum_{r=0}^{nu} w_{ir}x(t-r) + \sum_{l=1}^{ny} w_{il}y(t-1) + a_i\right] \tag{2}$$

Where w_{ir} is the weight of the link which connects the input node $x(t-r)$ and the i^{th} hidden node, w_{il} is the specified weight for the link which connect the i^{th} hidden node and output feedback node $y^T(t-1)$; while a_i is the specified bias of the i^{th} hidden node; while $f_1(\ )$ is the utilized activation function of the hidden layer.

Through considering the calculated output from the hidden layer, then the actual output can be predicted as given by [16]:

$$y_j^P(t) = f_2\left[\sum_{i=1}^{nh} w_{ji}H_i(t) + b_j\right] \tag{3}$$

Where w_{ji} is the weight value for connection between the i^{th} hidden neuron and j^{th} actual output n_h; b_j is the bias of j^{th} actual output; n_h is representing the total number of hidden nodes; and $f_2(\ )$ is the activation of the calculated output layer.

In any way, the number of hidden layers and their neurons should be determined to offer the best performance of network in training and testing [15, 17]. NARX's transfer function is exactly comparable to the essential back propagation neural network. When GPS signal is not available; we are trying to get an approximate location for objects using INS data. Therefore, INS data are presents the inputs of NARX neural network. We try to model the exact nonlinear assignment relationship with the unique information in which structures can be indirectly defined with the neural network. Finally, NARX neural network has been used to obtain the best prediction results about location. We can implement the NARX model

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that used for approximation of function in many ways, so the better and easier way is feed-forward neural network.

V. COMPARISON BETWEEN OPEN AND CLOSED ARCHITECTURES

Generally, there are two NARX architectures which are called a (1) series-parallel architecture type (open-loop),(2) parallel architecture type (close-loop). However, the training in open-loop architecture is faster and obtains better performance than the close-loop architecture, so the NARX network trained in series-parallel architecture and then it is converted to the parallel architecture to use for predicted the INS error. There are two equations for these architectures (2) and (3); respectively[18]:

$$\hat{y}(t+1) = f\left(y(t), y(t-1), \ldots, y(t-n_y), x(t+1), x(t), x(t-1), \ldots, x(t-n_x)\right) \tag{4}$$

$$\hat{y}(t+1) = f\left(\hat{y}(t), \hat{y}(t-1), \ldots, \hat{y}(t-n_y), x(t+1), x(t), x(t-1), \ldots, x(t-n_x)\right) \tag{5}$$

The $\hat{y}(t+1)$ is the NARX network output at the specified time t for the time $t+1$, $f(\ )$ represents the mapping function for the network. $y(t), y(t-1), \ldots, y(t-n_y)$ represents the actual outputs of time series. $\hat{y}(t), \hat{y}(t-1), \ldots, \hat{y}(t-n_y)$ are the estimated outputs of NARX network, $x(t), x(t-1), \ldots, x(t-n_x)$ are the NARX inputs. n_x represents the total number of input delays while n_y represents the number of output delays. Fig. 3 shows two architectures (open and closed loop) of the NARX network.

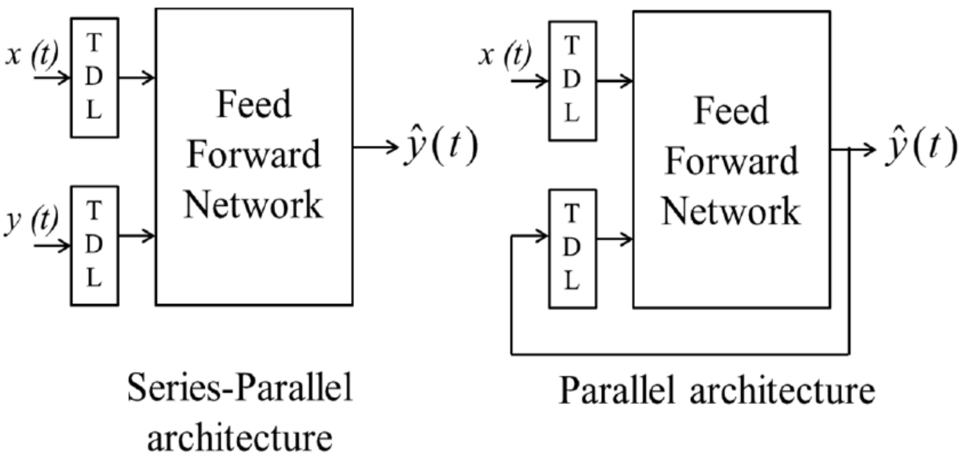

FIG. 3. THE ARCHITECTURES (OPEN AND CLOSED LOOP) OF THE NARX NETWORK [15]

During the training stage, the network must be enabled in the series-parallel (open-loop) architecture to train by using the actual output *y(t)* of the time series instead of the estimated $\hat{y}(t)$. There are two advantages of series-parallel architecture (open loop); the first advantage is the use of inputs for feed-forward network is more accurate and truthful. Secondly, the architecture of the resulting network is purely feed-forward and the back-propagation can be used for the learning algorithm [15].

VI. NARX NAVIGATOR DESIGN STEPS

The proposed NARX navigation system shall be designed according to the following three main steps:

A. Calculating the INS error signal step

To generate the INS error by subtracting the INS data from GPS data, which will be used as desirable output in the proposed NARX navigator. There are two characteristics of any neural network,

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training and testing. In general, the neural network works on learning so we do not program it, but we train it and then test it. That's why the training stage is considered as the most important characteristics of the neural networks.

B. Training mode for NARX neural network step

At the training mode, we estimate the parameters of the neural network in order to observe its performance of the work assigned to it. The training stage can only be effective after the accumulation of a set of inputs/outputs. According to the “learning algorithm”, the network weights cannot be modified in a random way. But when create a network, we considered that the inputs and outputs of neural network are stationary for the application to be accomplished, the weights of a neural network are adjusted through the training stage[17].

The fundamental function of the neural network proposed in this paper is feed-forward, back propagation. The number of layer in the neural network was determined when the computational complexity and avoid local minima are reduced after we apply many training tests. The computation was performed using raw GPS/INS data.

Fig. 4 shows the training mode for the NARX neural networks by utilizing both GPS and INS data to create an experimental sample of INS error for current and past value of INS data components for both velocity and position components, respectively. When GPS signal is available, the NARX Navigator system has been trained to estimate and predict INS error by computing the desired output (i.e. INS error) from subtracting the INS data components from the corresponding GPS data components for both the velocity and position and provide a precise navigation solution for the moving vehicle. To reduce the value of Mean Square Error (MSE), the learning parameters must be modified by comparing the actual output and the desired output while the result is a feedback to the NARX network.

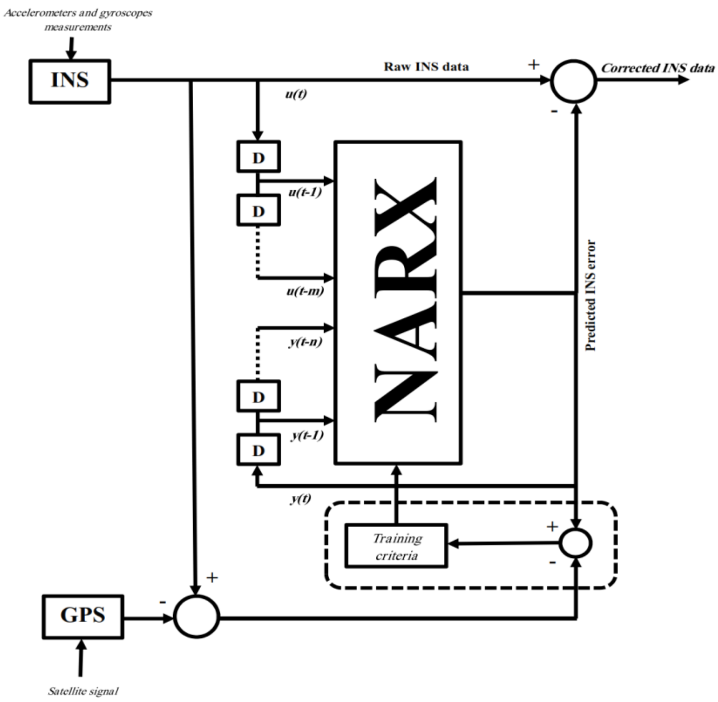

FIG. 4. NARX NEURAL NETWORK SCHEME DURING TRAINING MODE

Firstly, in this current work we predict the INS error with conventional neural network and secondly with NARX network. For this neural network we choose the INS data as an input and the INS error will be the output. To predict the value of INS error, the NARX model is based on the historical data that related to INS data and involves some exogenous data.

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C. Testing mode for NARX neural network step

The testing stage, also known as a population stage, is one of the properties that determine the performance of the neural network. After the learning mode is completed, the NARX neural network is ready to use in the testing mode by modeling both GPS/INS error and predicting the instant INS error.Fig.5 shows the operation of NARX in testing mode when the satellite signal is blocking. It provides a prediction of INS error based on the specific time available in the input INS data. From the corresponding INS data, we should remove the expected INS error to get an accurate position and velocity of the vehicle. Moreover, the performance comparison in this phase is conducted based on the Mean Square Error (MSE) as indicated in equation (6):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - y_i)^2 \quad (6)$$

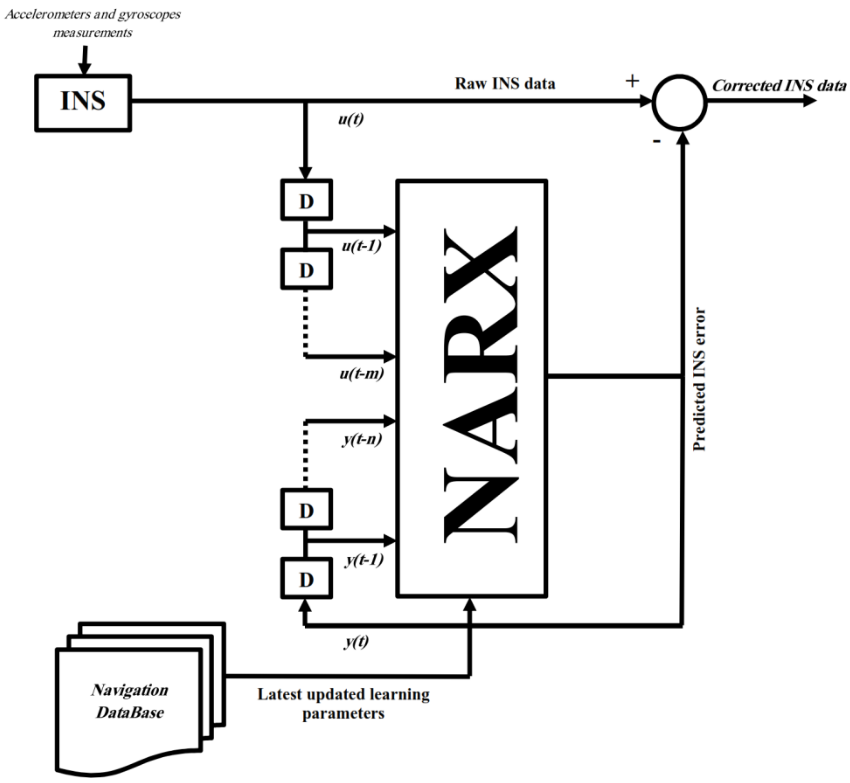

FIG. 5. NARX NEURAL NETWORK SCHEME DURING TESTING MODE

VII. RESULTS AND DISCUSSION

The influence of NARX network on the prediction of INS error is estimated based on both an instant and past value of INS data. According to the monitoring of the operation modes we perform a dynamic test of NARX. Firstly, during training mode we examined the NARX network to learn the INS error when the signal of GPS is available. In the second mode, when the signal of GPS is lost we must check the integrated system to verify the ability of the NARX model to provide a reliable and correct prediction for both, the position and velocity of an INS error.

Fig. 6 shows the INS error for *x*, *y* and *z*-axes that presented the position for (500 second).While Fig.7 shows the INS error for north, east and down direction that presented the velocity for (500 second), respectively. In these two figures, we noticed that the desired output is identical with NARX network as compared with conventional neural network. The results indicate clearly the superiority of NARX navigator compared to the conventional neural network.

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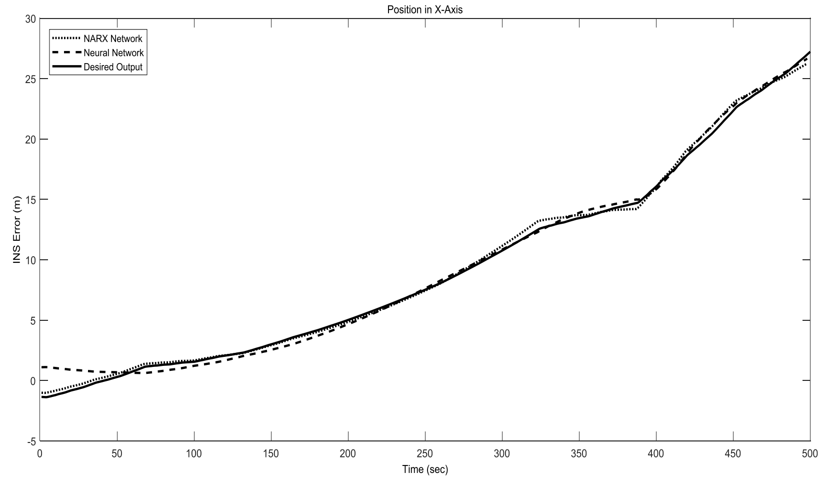
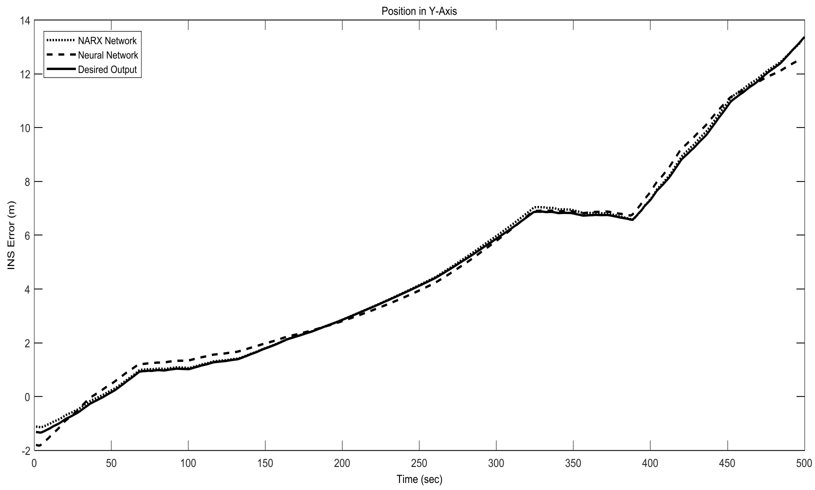


(A)



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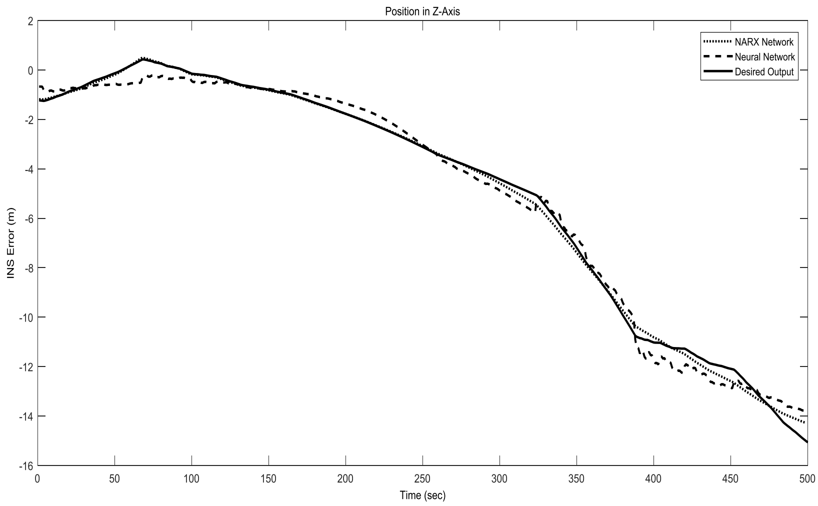

(C)

FIG. 6. INS ERROR FOR POSITION RESULTS THROUGH DIFFERENT GPS OUTAGES (A) X, (B) Y, AND (C) Z AXES

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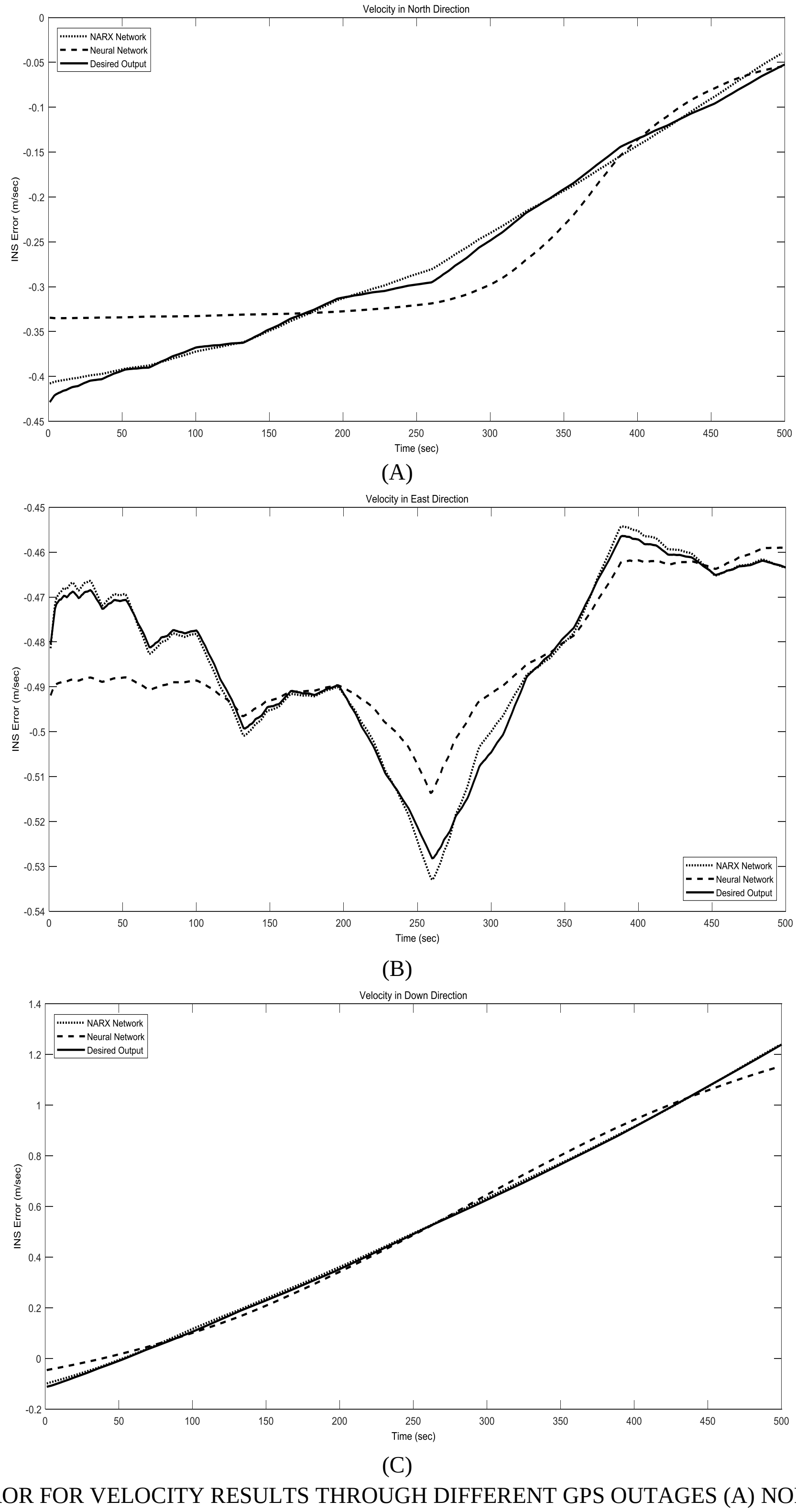

FIG. 7. INS ERROR FOR VELOCITY RESULTS THROUGH DIFFERENT GPS OUTAGES (A) NORTH, (B) EAST, AND (C) DOWN DIRECTION

The results of the proposed NARX and the conventional neural network were evaluated in terms of Mean Square Error, Minimum and Maximum error for the position and velocity as illustrated in table 1. The error that produced from the difference between the actual and desired output of the NARX network and classical neural network as shown in Fig.8 indicates the superiority of the proposed NARX for both, the position and velocity components when GPS signal is lost.

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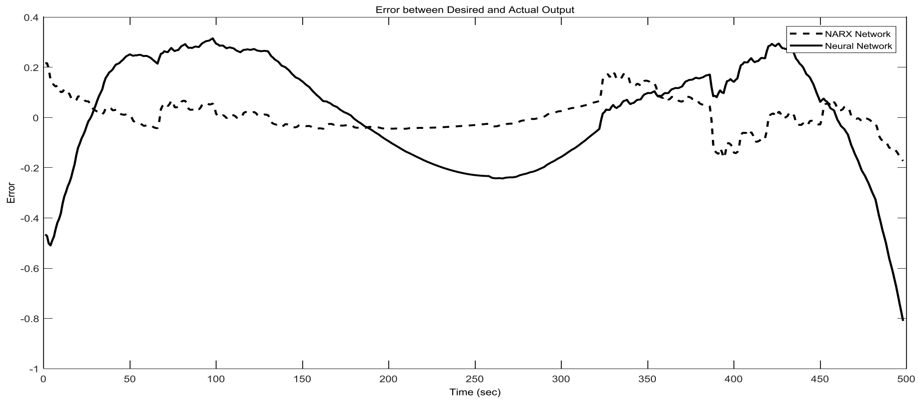
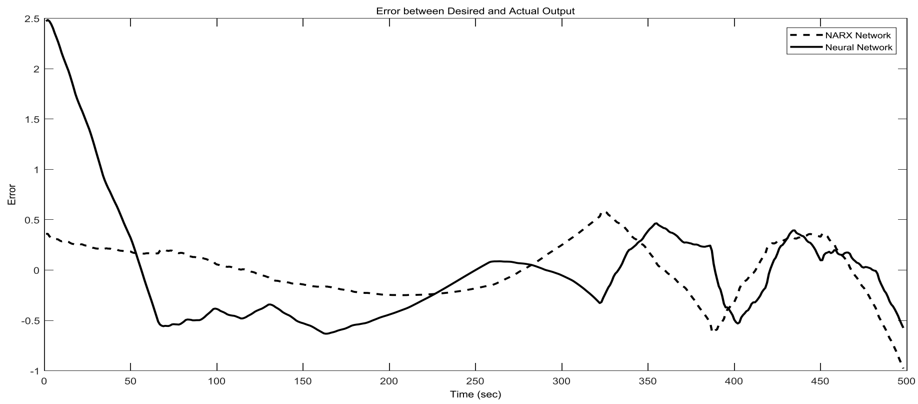
TABLE 1. PERFORMANCE COMPARISON BETWEEN THE PROPOSED NARX NAVIGATOR AND CONVENTIONAL NEURAL NETWORK.

Components		Method	MSE	Min Error	Max Error
Position	x-axis	CNN	0.37	0.23	0.45
		NARX	0.08	0.11	0.24
	y-axis	CNN	0.05	0.5	2.5
		NARX	0.013	0.031	0.8
	z-axis	CNN	0.2	0.63	1.25
		NARX	0.025	0.13	0.81
Velocity	North	CNN	1.4	0.02	0.09
		NARX	0.048	0.01	0.02
	East	CNN	0.1	0.006	0.017
		NARX	0.011	0.002	0.005
	Down	CNN	0.8	0.022	0.06
		NARX	0.036	0.01	0.02



(A)



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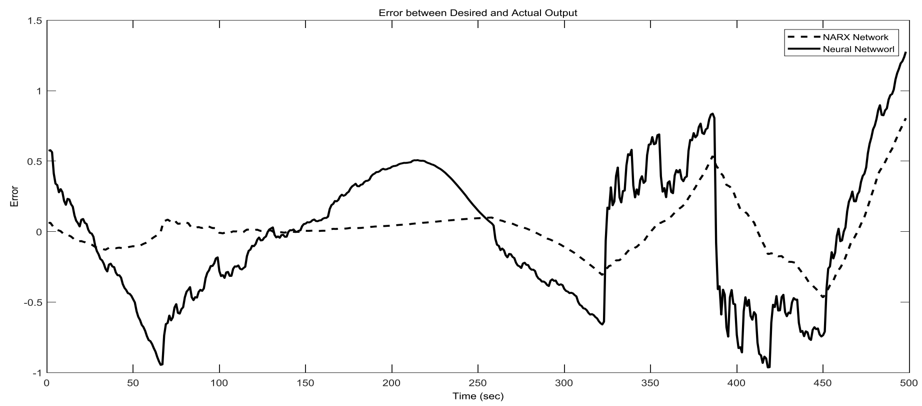

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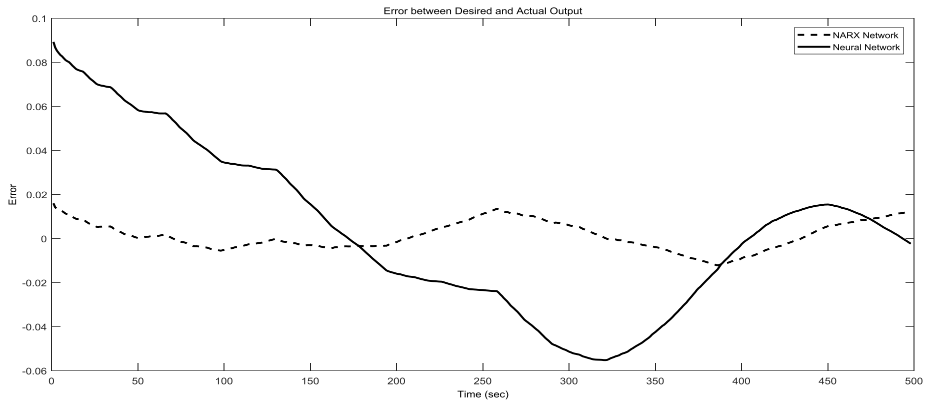

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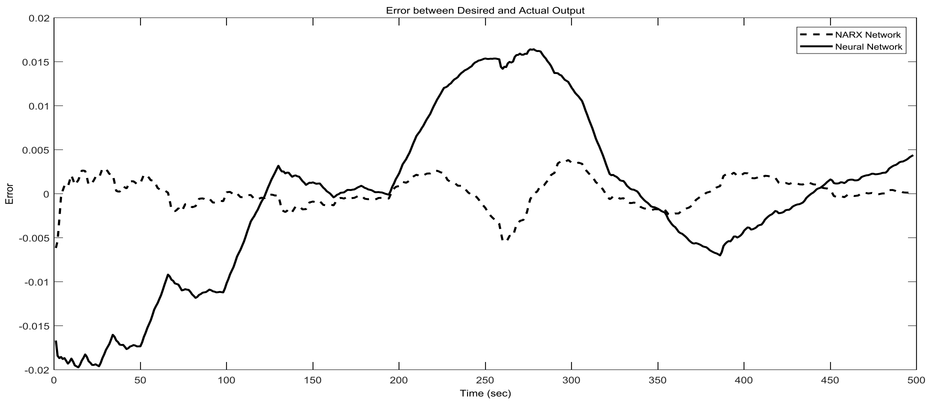
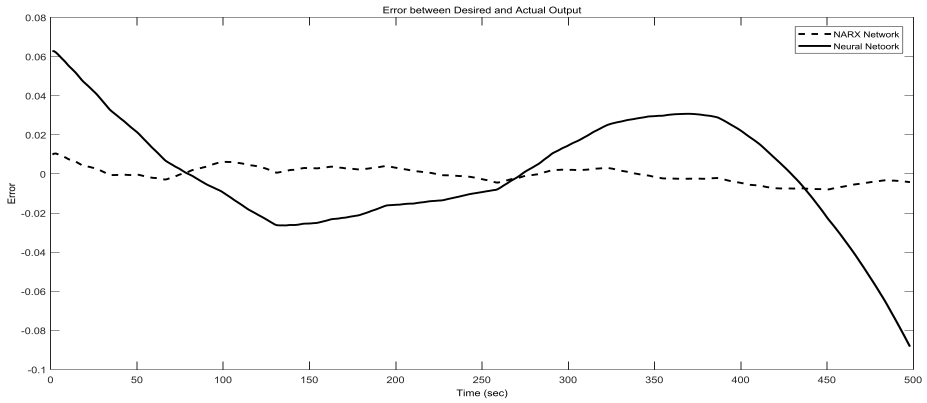


(E)



(F)

FIG. 8. ERROR BETWEEN ACTUAL AND DESIRED OUTPUT FOR POSITION AND VELOCITY, (A) X, (B) Y, (C) Z AXES, (D) NORTH, (E) EAST, AND (F) DOWN DIRECTION

Fig. 9 shows the number of delay from 1 to 14, we noticed that the MSE was reduced with increasing the elapsed time, so we chose number 8 as an acceptable accuracy number in terms of delay and time.

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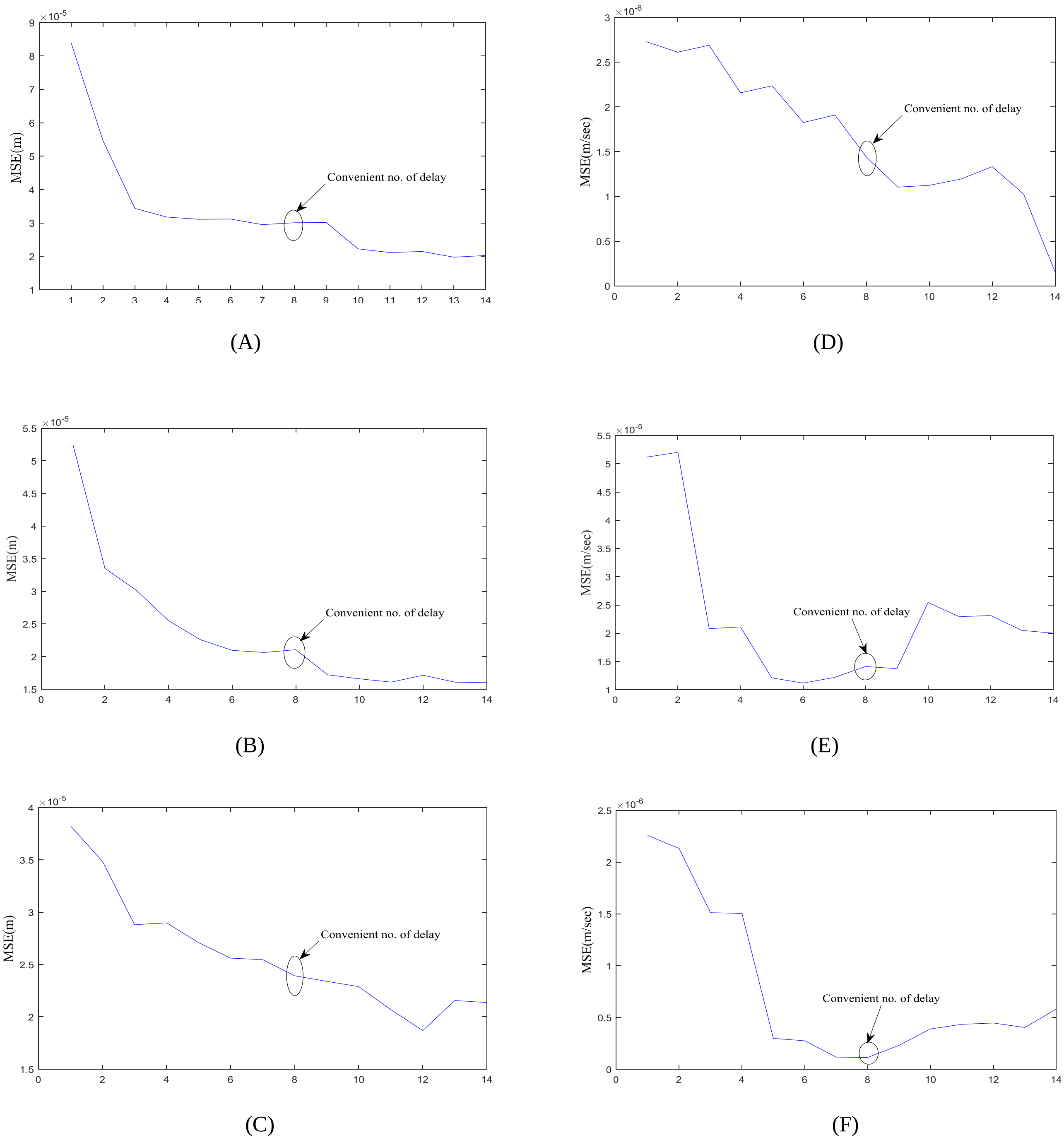

FIG. 9. VARIATION OF NUMBER OF DELAY AGAINST MEAN SQUARE ERROR FOR POSITION AND VELOCITY (A) X, (B) Y, AND (C) Z-AXES, (D) NORTH, (E) EAST, AND (F) DOWN DIRECTIONS RESPECTIVELY

VIII. CONCLUSION

A new module of NARX is introduced in this paper to predict and estimate the INS error by integrating both the GPS and INS navigation systems to address the restrictions of conventional approaches such as traditional Artificial Intelligent (AI) and Kalman Filter (KF) methods. Since NARX navigator that proposed depends on the immediate INS data that utilized to predict the consistent INS error when the signal of GPS is lost, the accuracy of prediction of INS error will be increased. The NARX navigator keeps learning as GPS signal is available for updating the navigator data base and starts to predict the instant INS error during the GPS signal is missing in order to keep the latest

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variations in the INS error over the time. The simulation results point out that the NARX navigator could effectively evolve the position accuracy as well as velocity and extend a precise navigation solution during GPS outages.

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