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A Study on the Performance of GA-Holt-Winters Model in 900 MHz Spectrum Prediction

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Abstract: **Continuous spectrum measurement is expensive and time consuming. This has necessitated the concept of spectrum prediction. Spectrum prediction uses historically observed data from spectrum sensing to forecast future channel states. In this research the suitability of the genetic algorithm modified Holt-Winters exponential model in the prediction of spectrum occupancy data was investigated. Minute spectrum duty cycle of selected locations in Ilorin, Nigeria was used in the evaluation of the forecast behaviour of the methods. It was observed that GA-Holt-Winter technique gave lower forecast values as evaluated from the Mean Square Error (MSE) serving as objective function in comparison with Holt-Winters method. The Holt-Winters method and GA-Holt-Winters technique were observed to be of good forecast behaviour with GSM 900 RL for both location. There was about 16% decrease in the MSE of GA-Holt-Winters technique compared to Holt-Winters in the GSM 900 RL for both locations. Finally, there was about 28% and 8% decrease in the MSE of GA-Holt-Winters technique compared to Holt-Winters in the GSM 900 RL for locations 1 and 2 respectively.**

Keywords: **Cognitive radio network, genetic algorithm, Holts-Winters exponential smoothing, spectrum occupancy, spectrum measurement, spectrum prediction.**

1. INTRODUCTION

Dynamic Spectrum Assess (DSA) technique have been proposed as a viable solution to spectrum allocation inefficiencies. With DSA secondary user should be able to utilize vacant channel opportunistically without preventing the licensed users from gaining access to the channel when desired. This demands a comprehensive understanding of spectrum utilization profile and dynamic behaviour of licensed users in a realistic scenario via spectrum measurement exercise. However, continuous spectrum measurement is expensive and time consuming. This has necessitated the concept of spectrum prediction. Spectrum prediction uses historically observed data from spectrum sensing to forecast future channel states (Yang & Zhao, 2015). Several techniques have been used to predict future spectrum states such as neural network (Zhang *et al*. 2019), markov model (Zhao *et al*. 2016), Bayesian inference (Jacob *et al*. 2014), static-neighbour-graph (Bütün *et al*. 2010) and time series models (Safari, 2017).

The GA or its variant extension of Holt-Winters method have been used by different authors in forecasting in diverse field. Peng *et al*. (2019) used a niching GA and HW method to predict "mining subsidence" crucial "in engineering construction over underground mines." The relative prediction errors were less than 2% and the mean error was -0.18%. The authors reported that this was a better performance than the Support Vector Machine (SVM) based predictive technique. Amzi (2013) used GA to estimate the Holt-Winter parameters when forecasting tourist arrival data in Langkawi Malaysia. The results of the GA outperformed the conventional optimization approaches, in terms Mean Average Percentage Error.

The HW method permits one to correctly predict seasonal series with comparatively small training samples. With the use of this technique, a hybrid predictive model is proposed to forecast spectrum occupancy. The GA is used to optimize the smoothing parameters for the HW technique.

The paper is outlined as follows: in Section 2, the GA-Holt-Winters models are presented using equations, flowcharts and algorithms. Section 3 presents a description on the software and machine configurations used in the study. The results obtained are reported and discussed in Section 4.

2. METHODOLOGY

2.1. The Genetic Algorithm

Genetic algorithm commences with a string population and consequently produce other generation of population of strings in accord with specific nature inspired operations of reproduction, crossover and mutation .

The operation of ***Reproduction*** allows for the retaining parent "chromosome and transfer" of same to the offspring, a set of improved solutions. In this case there is no change to the chromosome. That is, the output of this process is the same as the input. This usually leads to a local optimal (Peng *et al*., 2019 & Metawa *et al*., 2017).

In ***Crossover*** operation two chromosomes are concatenated to generate two new chromosomes through the process of gene switching. For "a simple one-point crossover operation for" binarized population. For example, if two strings in the current population P are I and I', then (Peng *et al*., 2019 & Metawa *et al*., 2017),

$$I = \{x_1, \ldots, x_j, \ldots, x_n\} \tag{1}$$

$$I' = \{x'_1, \ldots, x'_j, \ldots, x'_n\} \tag{2}$$

The crossover point is fixed through the random generation an integer j from 1 to n. The resulting cross indexes are eqns. (3) and (4) (Metawa *et al*., 2017):

$$I = \{x_1, \ldots, x_{j-1}, x'_j, \ldots, x'_n\} \tag{3}$$

$$I' = \{x'_1, \ldots, x'_{j-1}, x_j, \ldots, x_n\} \tag{4}$$

Mutation, in contrast with reproduction and cross-over involves the reversing "the value of one gene" of "a chromosome" in a random manner, resulting in a different but mutated output. Let s_j be randomly selected, which mutate in x'_j, if $x_j = 1$ then $x'_j = 0$ and if $x_j = 0$ then $x'_j = 1$. This GA operation creates a completely new species, in so doing it help in getting out of local optimum by the creation of an arbitrary locus (Peng *et al*., 2019 & Metawa *et al*., 2017).

The flowchart for the implementation of GA is shown in Figure 1.

2.2. Holt-Winters Method

It is assumed that the seasonal time series model is:

$$y_t = L_T + \varsigma_t + \varepsilon_t \tag{5}$$

where L_t = the linear trend component, which can be represented by:

$$\beta_0 + \beta_1 t : \beta_0, \beta_1 \in \mathbf{Z} \tag{6}$$

ς_t = the seasonal adjustment with $\varsigma_t = \varsigma_{t+m} = \varsigma_{t+2m} = \cdots$ for $t = 1, \ldots, m-1$

where m = the period length of each cycle; and the error ε_t are taken to be "uncorrelated with zero mean and constant variance σ^2." As mentioned in Section 1, seasonal components sum up to zero during one cycle, that is;

$$\sum_{t=1}^{m} \varsigma_t \qquad (7)$$

The Holt-Winters method calculates dynamic estimates for three components, namely, the level (L_t), trend (T_t), and seasonality (ς_t), either using the additive model or multiplicative model [24, 38, 42]. The procedure for updating the parameter estimates once the current observation y_t is obtained eqns. (8) - (15).

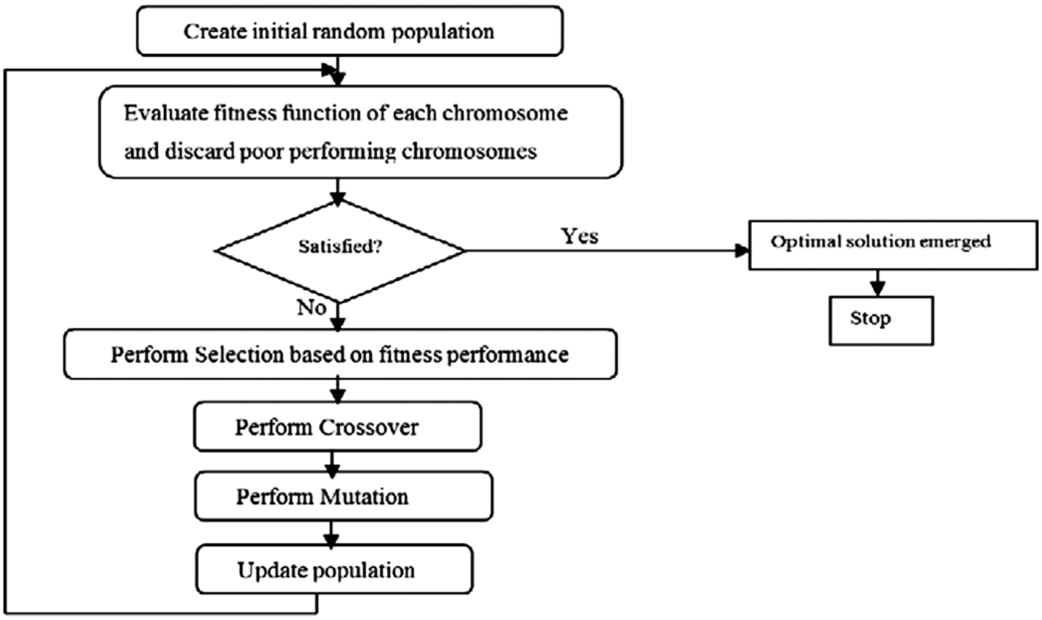

Figure 1: Flowchart of genetic algorithm (Sourced from Chiroma et al. 2016)

he additive model is as shown in eqns. (8) - (10):

$$L_t = \alpha(y_t - \varsigma_{t-s}) + (1-\alpha)(L_{t-1} + \mathrm{T}_{t-1}) \qquad (8)$$

$$\mathrm{T}_t = \gamma(L_t - L_{t-1}) + (1-\gamma)\mathrm{T}_{t-1} \qquad (9)$$

$$\varsigma_t = \delta(y_t - L_{t-1} - \mathrm{T}_{t-1}) + (1-\delta)\varsigma_{t-m} \qquad (10)$$

The forecast value is given in eqn. (11):

$$\hat{y}_t = L_{t-1} + \mathrm{T}_{t-1} + \varsigma_{t-m} \qquad (11)$$

The multiplicative model is as shown in eqns. (12) - (14):

$$L_t = \alpha(y_t / \varsigma_{t-m}) + (1-\alpha)(L_{t-1} + \mathrm{T}_{t-1}) \qquad (12)$$

$$\mathrm{T}_t = \gamma(L_t - L_{t-1}) + (1-\gamma)\mathrm{T}_{t-1} \qquad (13)$$

$$\varsigma_t = \delta\left({}^{y_t}/_{(L_{t-1} + T_{t-1})}\right) + (1-\delta)\varsigma_{t-m} \qquad (14)$$

The forecast value is given as:

$$\hat{y}_t = (L_{t-1} + T_{t-1})\varsigma_{t-m} \quad (15)$$

where α, γ and δ are discount factors ranging [0,1]. An initial value of 0.2 is selected for all three discount factor.

In this study, various values for the seasonal period are investigated. The period that results in the least mean square deviation (MSD) will be selected for further optimization using the GA. The expression for computing the MSD is given in eqn. (16).

$$MSD = \sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|^2}{n} \quad (16)$$

where y_t = the true value, $\hat{y}_t$ = the corresponding fitted/predicted one with n observed samples.

2.3. Genetic-Holt-Winters Algorithm

The genetic algorithm is used to determine the optimal values of α, γ and δ such that the forecast errors are minimized. If α, γ and δ are too small oversmoothing takes place and if they are closer to one, no smoothing takes place. The procedure followed are itemised as follows and the flowchart is shown in Figure 2 (Peng *et al*. 2019):

(1) Initialisation the GA parameters e.g. population size and evolution number.

(2) Initialisation and interval selection of the the HW smoothing parameters α, γ and δ.

(3) Evaluation the objective function e.g. Mean Square Error (MSE) between the predicted data and the spectrum occupancy as may be seen in eqn. (17).

(4) Evaluate the fitness for each individual in the niche, and then select the best one in the niche to the next generation .

(5) Optimise the parameter by minimising the MSE using GA operations described in Section 2.1.

$$f = \min \frac{\sum_{i=1}^{n} (y_t - \hat{y}_t)^2}{n} \quad (17)$$

$$s.t. \alpha, \gamma, \delta \in [0,1] \quad (18)$$

Equations (19)-(21) were used to determine the initilisation values of the levels, trend, and seasonality index.

$$L_0 = n^{-1} \sum_{t=1}^{n} y_t \quad (19)$$

$$T_0 = N \quad (20)$$

$$S_0 = \frac{\bar{y}_m}{L_0} \quad (21)$$

where

N is a selected integers and $\bar{y}_m$ is the average of a selected period samples

The goal is to find the set of parameters α, γ and δ that minimises MSE.

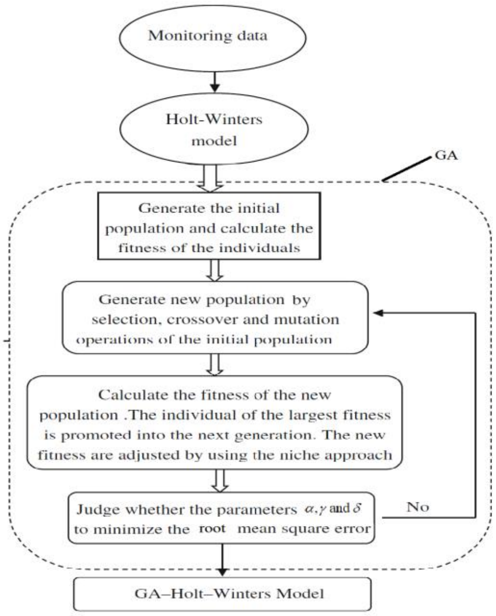

Figure 2: GA-Holt-Winters model flowchart

2.4. Spectrum Occupancy Dataset

a. Measurement Set Up

The experimental setup consists of energy detector, a field strength analyser (BK PRECISION 2640) with 100 kHz – 2.0 GHz frequency range, Omni-directional antenna, mobile phone-based GPS. The GPS enables the determination of the coordinates of each location (Loc. 1 and Loc. 2) spectrum measurement. The procedure recommended in ITU-R SM 2256-1 (2016) was followed in determining spectrum occupancy with regards to measurement steps and revisit time.

b. Data Processing

The procedure followed in processing the collected data is as shown in Figure 3.

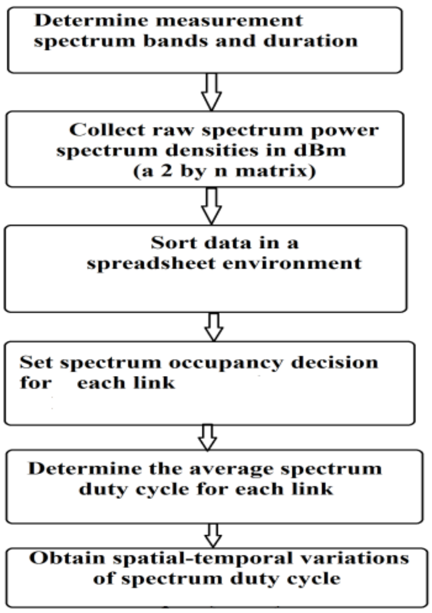

Figure 3: Data processing procedure

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2.5. Experiment setup

Under this section of the article, a presentation of the design and setting of the machine used in the experimentation is given. The fitness function adopted for the study with justification is explained. Further, GA-Holt-Winters model parameters are initialised, the running of the proposed GA-Holt-Winters model, and the comparison method such as the unmodified Holt-Winters model are discussed.

c. Settings and Design of Experimentation Machine

The GA-Holt-Winters model advanced in this research is used to predict spectrum occupancy data. The result of GA-Holt-Winters model is compared with that of the unmodified HW model. The GA-HW technique is implemented in Microsoft Excel 2016 Solver and MATLAB R2018a on a machine configured as follows: Intel Core i5, CPU 2.88 GHz, RAM 8 GB, 64-bit operating system .

The MSE is used as the objective function to determine the GA-Holt-Winters model's accuracy in forecasting spectrum occupancy. The MSE provides an estimate of the error between the true spectrum occupancy and that forecast by the GA-Holt-Winters model. The closer MSE is to 0, the more accurate the prediction model.

d. Initialization of the GA-Holt-Winters model parameter settings

For the GA: "population size = 20, crossover rate = 1, mutation rate = 0.1" and the number of evolution = 1000. The initial discount factors are set at 0.3 each.

3. RESULTS AND DISCUSSION

Here, the results obtained from the models presented in Section 2 are reported and analysed.

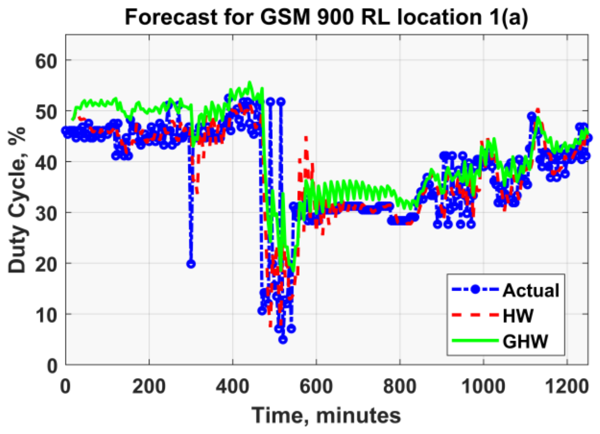
3.1. Selection of the Choice of Period

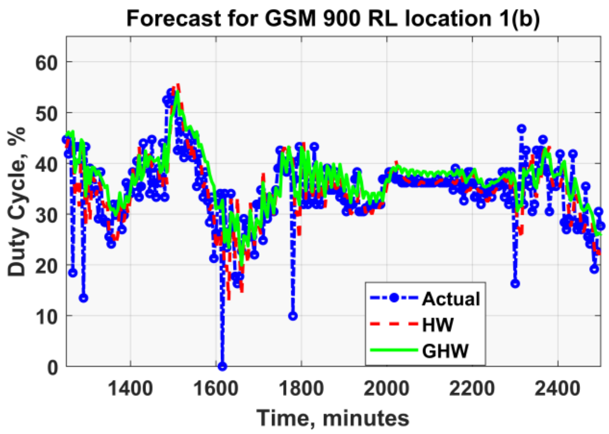
To determine the period number best suited for the forecast, the (MSD) for when the period is 3, 6, 9 and 12 were evaluated. The MSD at 3 period are consistently the lowest in each band and link considered as may be seen from Table 1. The MSD for all link for when period is 3 and 12 varied by up to 12% for GSM 900 RL in both locations

Table 1: Mean Absolute Deviation of spectrum duty cycle of selected links

Bands/Links	Mean Absolute Deviation at selected period			
	3	6	9	12
GSM 900RL LOC1	4.00	4.23	4.40	4.56
GSM 900RL LOC2	1.96	2.08	2.14	2.21

3.2. Prediction Results





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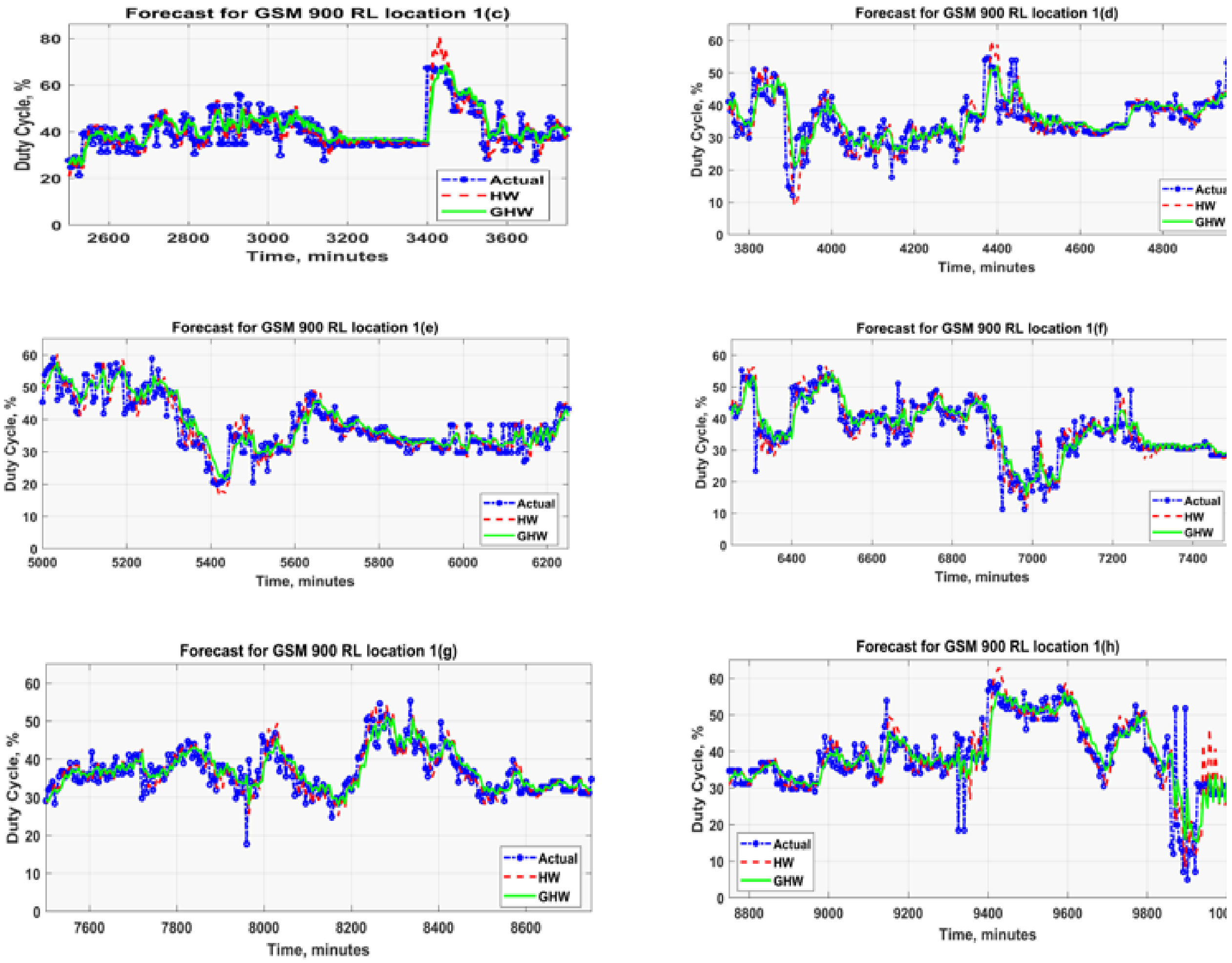
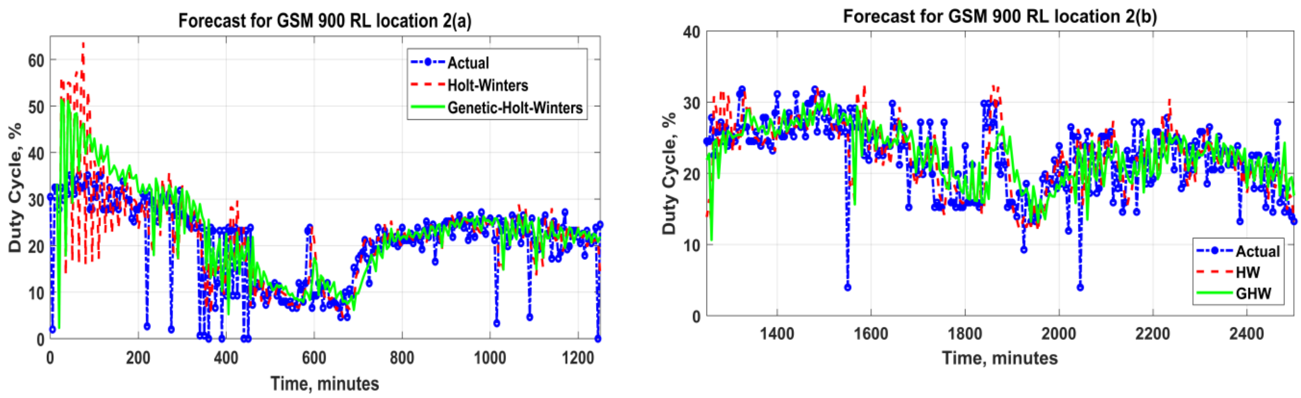


Figure 4: Forecast for GSM 900 RL location 1

There is a good forecast of spectrum duty cycle of the links considered. The exception was in GSM 900 FL for both locations. This was due to these spectrum links being characterised with several vacancies. For other links, the MSE obtained are shown in Table 2. Consistently, The MSE values obtained for GA-Holt-Winters were lower than that of Holt-Winters.

The data for each location was divided into eight portions (a-h) to allow for less clumsy plots and easier understanding. This is seen from Figures 4 and 5.



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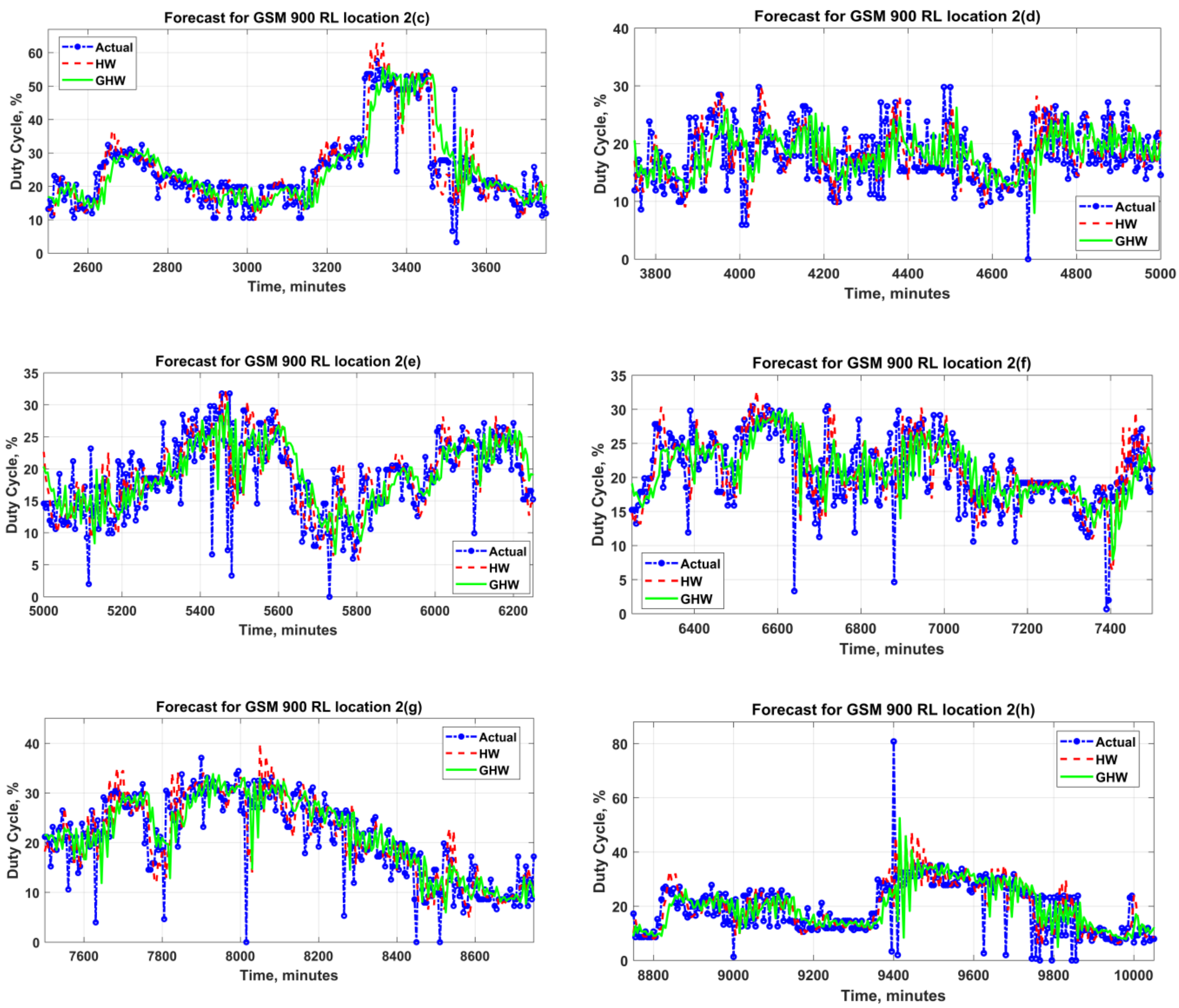

Figure 5: Forecast for GSM 900 RL location 2

Both the Holt-Winters approach and the GA-Holt-Winters strategy were shown to have acceptable forecast behavior for both locations using GSM 900 RL. In both sites, the MSE of the GA-Holt-Winters approach was around 16 % lower than that of Holt-Winters in the GSM 900 RL. Finally, the MSE of the GA-Holt-Winters approach in the GSM 900 RL for sites 1 and 2 decreased by roughly 28 and 8 %, respectively, in comparison to Holt-Winters.

Table 2: Comparison of MSE of selected links

Bands/Links	Forecast Mean Square Error	
	Holt-Winters	GA-Holt-Winters
GSM 900RL LOC1	36.34	30.51
GSM 900RL LOC2	8.91	7.56

The discount factors, which were modified in the implementation of the GA-Holt-Winters are shown in Table 3. The initial values used were 0.30 each. For GSM RL 900 RL location 2, GSM 1800 RL location 1 and GSM 1800 FL location 1, there were no trend components.

Table 3: Obtained discount factors for minimum MSE of forecast links

Bands/Links	Discount Factors		
	α	γ	δ
GSM 900RL LOC1	0.31	0.00	0.11
GSM 900RL LOC2	0.47	0.00	0.01

4. CONCLUSION

Spectrum prediction is motivated by the knowledge that continuous spectrum measurement is expensive and time consuming. In spectrum prediction historical data from spectrum sensing are used in forecasting future spectrum states. In this research the suitability of the GA modified Holt-Winters exponential model in the prediction of spectrum occupancy data was investigated. The Holt-Winters method and GA-Holt-Winters technique were observed to be of good forecast behaviour with GSM 900 RL for both location. There was about 16% decrease in the MSE of GA-Holt-Winters technique compared to Holt-Winters in the GSM 900 RL for both locations. Finally, there was about 28% and 8% decrease in the MSE of GA-Holt-Winters technique compared to Holt-Winters in the GSM 900 RL for locations 1 and 2 respectively.

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