VISIBILITY FORECAST VERIFICATION AT JOMO KENYATTA INTERNATIONAL AIRPORT.

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RESEARCH PROJECT SUBMITTED TO THE SCHOOL OF PHYSICAL SCIENCES, DEPARTMENT OF METEOROLOGY IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF A POST GRADUATE DIPLOMA IN AVIATION METEOROLOGY, UNIVERSITY OF NAIROBI.

JULY 2013

DECLARATION

Declaration by the candidate

I declare to the best of my knowledge that this is my original work and has not been submitted for award of degree in any university or institution of higher learning or anywhere else.

Signature.. Date..................................

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Declaration by the supervisors

This research project has been submitted for examination with our approval as university supervisors

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This work is dedicated to my dear daughter (Delphyl) who should be encouraged to work tirelessly to achieve great heights in education.

ABSTRACT

The economic growth of any airline is largely determined by the optimum operationalization of the flight schedules. Bad weather and in particular low visibility at the airport may lead to interruption of the schedule. Low visibility may also lead to delays for several hours when taking off and holding for some time or diversion. Diversions to nearby airport lead to large economic losses to the airline.

Visibility forecasts are very critical in flight planning hence considerable interest in assessing its accuracy, skill and value. The visibility forecasts form part of the Terminal Aerodrome Forecast (TAF) provided by aerodrome meteorological office.TAF comprises of forecast for wind speed and direction, visibility, weather and ceiling conditions. In this research the forecasts for visibility was verified against visibility observation for 0hr and 6hr lead times. The lowest observed value was used to score against the lowest forecasted value. Visibility was categorized into ranges of poor covering range between 0-1000m, fair between 2000-4000m and clear between 5000-9999. The entries were then made into a 3-category contingency table for six hour lead time. Accuracy at 0hr and 6hr lead time was evaluated using the scatter plot and the root mean square error for days with determinable visibility both in the forecast and in the observations, visibility of 9999 were dropped since specific visibility value could not be determined. Various skill score were then evaluated from the contingency table.

The accuracy and skill scores for visibility forecasts are high for 0hr lead time as compared to 6hr lead time hence the visibility forecasts should be used immediately after production and limited to not more than six hours since its accuracy and skill drops drastically. For flight planning the new and amended forecasts should be treated with urgency since convey more accurate forecasts.

The verification results should be able to show the strengths and weaknesses attached on the visibility forecasts thereby acting as a tool to foster further improvement in low visibility forecasting on the part of the forecasters. The skill scores generated from the contingency table will assist the management in advancing ways of improving low visibility forecasting by improving the equipments for observing and forecasting low visibility and also initiating further training in low visibility forecasting for forecasters.

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LIST OF ACRONYMS

ATM	Air Traffic Management
BECMG	Becoming (used in TAF code)
BKN	Broken (5-7/8 cloud cover; used in METAR and TAF code)
BR	Mist (used in METAR and TAF code)
CB	Cumulonimbus cloud
CSI	Critical Success Index
E	Event
F	False alarm rate
F.A.R	False Alarm Ratio
FCST	Forecast
FM	From
GGgg	Time statement
GS	Gerity Score
H	Hit rate (probability of detection POD)
HSS	Heidke Skill Score
ICAO	International Civil Aviation Organization
JKIA	Jomo Kenyatta International Airport
KAA	Kenya Airports Authority
KCAA	Kenya Civil Aviation Authority
KMD	Kenya Meteorological Department
MET	Meteorological

METAR	Meteorological aviation routine weather report
OBS	Observed
ORSS	Odds Ratio Skill Score
OVC	Overcast
p(E)	Base rate; probability of event E when being forecast, when not being forecast
PC	Percentage Correct
POD	Probability of Detection (hit rate)
PROB	Probability forecast
PSS	Pierce’s Skill Score
RA	Rain
RE	Recent weather
RVR	Runway Visual Range
SPECI	Special weather report in METAR code
TAF	Terminal Aerodrome Forecast
TCU	Towering Cumulus
TEMPO	Temporary
THS	Threat Score
TS	Thunderstorm
TTF	Trend Type Forecast
UTC	Universal Time Coordinated
VC	Vicinity

VIS Visibility

VRB Variable wind direction

VV Vertical Visibility

WMO World Meteorological Organization

CHAPTER ONE

1.0 INTRODUCTION

Visibility forecasts are very critical in flight planning hence a considerable interest in assessing the accuracy, skill and value. The visibility forecasts are contained in the Terminal Aerodrome Forecast (TAF) produced by the designated meteorological office. The TAF contains the precise statement on the expected conditions of wind direction and speed, visibility, significant weather and ceiling conditions. Visibility is considered most critical to aviation operations (Mahringer 2008). Low visibility at the airport may lead to delays for several hours during taking off and holding for some time and consequential diversions to a nearby airport during the final phase of landing. The delays, holding and diversion actions bear huge economic impacts on the aviation operators. The impact is considered great due to the abruptness in occurrence and Rudek et al (2010) elude the challenges in low visibility forecasting to the difficulty in modeling the conditions and various meteorological processes that lead to the occurrence of low visibility. Due to the impact of low visibility to the aircraft operations it is of considerable importance to improve the skill for its forecasting. According to Fabbian et al (2006), the economic value for aviation forecast for Sydney airport in 1993 was estimated at 6.8 Australian dollars for Quantas airways only.

Low visibility can be caused by fog and/or low clouds, drizzle, heavy rainfall, dust storms and/or haze and smoke and smog from wild fires. According to Muiruri (2006, 2011) and Mwebesa (1981), much of the low visibility instances at Jomo Kenyatta International Airport are mainly associated with fog occurrences compared to other factors.

Verification of the forecast depends entirely on the quality of the observable data. The bone of contention for concern apart from the quality of data is the treatment of change groups in the forecast and scores allocation at each time. The TAF employs the use of change groups like BECMG for transition within a time interval, FM for transition beginning at a specified time, TEMPO for temporary changes and PROB for changes expected with a certain probability usually a probability of 30% or 40% is employed in the TAF. The controversy in visibility forecast verification comes with the use of these change groups. The forecast is not for an isolated time but a range of time interval hence one cannot directly compare observed conditions at a single time with what was forecasted since there is more than one forecast state valid for many points of time in a TAF. This challenge calls for the use of blocks of time usually six hours for JKIA as per the nature of the forecast. The low visibility is considered an extreme event hence the worst observed within the time interval is compared with the worst forecasted within that time interval. Mahringer (2008) defines the Operational Impact Forecast as the forecast in effect that is most likely to have a large impact on flight operation hence uses a very complex approach to verification TEMPO. A forecast is correct as long as the observed value lies within the range opened by the TEMPO since the forecast in this case is given as a range of possible conditions within a defined time interval. Considering the forecast as range of possibilities within a time interval assists in overcoming the problem coming with the idea of point verification. Averaging the observed value within the time interval introduces more noise since the forecast on visibility gives the worst expected situation within a time interval and it can occur at any time within the interval. The accuracy is determined basin on the operationally desired accuracy of forecasts as contained in the appendix B (ICAO Annex3, 2010).

This project is aimed at establishing the accuracy and skill for forecasting visibility at Jomo Kenyatta International Airport as a tool for low visibility forecast accuracy improvement and confidence building.

1.1 STATEMENT OF THE PROBLEM

The low visibility leads to diversions, delays and flight cancellations which have great economic implications to the aviation operators. The abrupt change of schedules, cancellations, diversions and delays due to abrupt occurrence of poor visibility calls for verification so as to assessment of accuracy and skill of the visibility forecast.

1.2 RESEARCH OBJECTIVES

1.2.1 OVERALL OBJECTIVE

The primary objective of this project is carry out the verification of the low visibility forecasts produced for Jomo Kenyatta International Airport to determine the accuracy and skill of visibility forecasts.

1.2.2 SPECIFIC OBJECTIVES

- **i.** Assess the accuracy of visibility forecasts at Jomo Kenyatta International Airport
- **ii.** Asses the skill for forecasting visibility at Jomo Kenyatta International Airport

1.3 RESEARCH QUESTIONS

- **a)** What is the accuracy of visibility forecast for Jomo Kenyatta International Airport?
- **b)** What is the skill for forecasting visibility at Jomo Kenyatta International Airport?

1.4 HYPOTHESIS

Visibility forecasts produced at Jomo Kenyatta International Airport meets the required quality.

1.5 JUSTIFICATION OF STUDY

The accurate visibility and more importantly low visibility forecasting can assist greatly to the safety, efficiency and regularity of the international air navigation. This will ensure proper and accurate flight planning thus reducing the expenses on fuel due to diversions and also reduce instances of delays and holding. The International Civil Aviation Organization requires each aviation meteorological provider to be ISO certified and forecast verification is a crucial ingredient towards ISO certification (ICAO Annex 3, 2010). Muiruri (2006, 2011) and Mahringer (2008) recommended for the assessment of the aviation forecast accuracy.

1.6 STUDY AREA

1.6.1 LOCATION

The study was conducted at the Jomo Kenyatta International Airport situated in Nairobi the capital city of Kenya. The airport is neighbored by the industrial area to the North. It is situated on latitude 01^0 19’S and longitude 36^0 55’E and has an elevation of 1624m above sea level with standard pressure of 840MB at 0600Z.

1.6.2 TOPOGRAPHY

The airport is located on a flat land, adjacent to Nairobi is the Ngong hills which has four peaks and very crucial to aviation operations acting as a beacon for navigation purposes.

1.6.3 CLIMATE

Jomo Kenyatta international airport experiences two rain seasons, the long rain season during March to May and the short rain season from October to December. The rain seasons in this region depends entirely on the position and annually movement of the ITCZ. The two rain seasons occurs during the monsoon transition periods. The area has a mean annual rainfall of 762mm and a mean of 27 thunderstorm days in a year (Muiruri, 2011).

CHAPTER TWO

2.0 LITERATURE REVIEW

Forecast verification is a major tool that can be used to improve the accuracy and confidence placed on the forecasts hence reducing the expenses incurred on diversions and delays by the airlines. Muiruri (2010) concurs that forecast accuracy is very vital to the pilot since it assists not only in planning the flight but even at decision making point whether to land or not. According to Mahringer (2008) unexpected visibility below minimum threshold affects the airport operations to a larger extent. Airport operations are adversely affected by adverse weather and therefore timely information on sudden weather changes is required to guarantee safety, efficiency and regularity of air transport. According to Muiruri (2010) among the adverse weather phenomenon affecting airport operations at JKIA low visibility is ranked the highest. The same fact is supported by Mahringer (2008) he states that 'the most important parameter in the numerical guidance is visibility. Poor visibility occurs due to the presence of the suspended droplets and/or crystals that render an object undistinguishable to a distant observer. The poor visibility occurs through the reduction in brightness contrast between an object and its background by particle concentration and size. The size and concentration of the particles can lead to partial or total atmospheric obscurity. On the other hand the obscurity could be caused by the scattering of the sun rays due to the presence of the droplets and/or crystals thus causing the blurring of the objects to the observer. Atmospheric obscurity can be caused by the concentration of hygroscopic nuclei, small and large water droplets, fine sand and smoke and smog. The concentration of these particles tends to reduce the distance through which an observer can see and identify an object situated some distance away from the observer.

Verification of forecasts is very important in operational forecasting. It assists in establishing the accuracy, skill and value of the forecast. Benedetti (2010) argues that effective verification scheme can go a long way in enhancing the improvement of skill of forecasting and consequential usage of the forecast for economic importance. As earlier explained poor visibility is caused by concentration of particles in the atmosphere, the Jet-carbon exhaust contributes greatly to the instances of poor visibility (Mcdonald 1962), hence need for its investigation. The abruptness related to the occurrence of low visibility makes its forecasting difficult and hence it is a threat to the aviation operations.

Visibility is very important to the pilot intending to land or take off from an aerodrome. The pilot intending either to take off or land at a particular aerodrome is required to see the runway markings well enough so as to embark on either of the tasks. One of the adverse weather having great impact on the aviation industry at Jomo Kenyatta international airport as Muiruri (2010) agrees is the low visibility. The decision to land or take off by the pilot is not made by incorporates the views from the traffic controller who directs the pilot on maneuvering either before take-off or after landing at an airport. From this point of view as much as it is important for the pilot to be in good visibility consequently it is equally very important for the tower traffic controller to be in best visibility. With advance in technology some aero planes are now fitted with instruments to assist in landing. Goteman (2007), shows that even during these instances the safety depends entirely on the current visibility range over the runway complex, in his work he describes the use of head up display (HUD) as an instrument for landing in low visibility. Looking at the San Francisco International Airport Renolds et al (2012) notes that poor visibility can reduce the arrival traffic by half compared to normal days. The importance of visibility in air transport has seen the development of visible enhancing tools as Kramer et al (2008) describes to be used by the pilot especially for landing in low visibility. He further explains that the improved forecasting of clearance of low visibility can lead tremendously to reduction on arrival delays thus substantially contributing to the monetary savings to the airlines.

Fog can be defined as clouds forming very close to the ground that reduces visibility to less than a kilometer. At Jomo Kenyatta international airport Mwebesa (1981) shows that fog occurs between 2100Z and 0700Z with prevalence between 0200Z and 0500Z. The problem with fog lies in the technicality of its forecasting as Roquelaure (2008) agrees with the fact that forecasting phenomenon which is on a meso scale factor is very difficult especially when it involves short range forecasting, this encompasses fog forecasting. Fog is considered to bear great effect on the visibility in many parts of the world as Jenamani et al (2011) deduces. The challenge experienced with reduced visibility owes to challenges faced in forecasting fog. Gultepe (2009) states that, if fog can be accurately and timely forecasted then the economic value lost due to sudden occurrence of fog in form of delays and diversions will be reduced. Fog occurrence poses serious challenges to the air operators. As Gultepe (2007) notes, the financial and human losses related to fog and low visibility is now comparable to losses from tornadoes and hurricanes. This prompts the need to improve its forecasting and issuance of early warning of its occurrence. The intensity of fog depends entirely on the amount of liquid water droplets contained in the low level cloud while the vertical and horizontal distribution of cloud water in the stratiform boundary layer clouds defines the intensity of fog formation (Tjernsrom, 1992). The injection of moisture into the cloud much closer to the ground can eventually result into formation of very dense fog. The calm situation or low speed winds reduces the mixing depth over which fog forms.

Accurate forecasting of visibility can assist the pilot in planning the flight well hence reducing the cost of fuel on delays and diversions at the airport. The sudden changes in visibility have proved a challenge towards accurate low visibility forecasting. As Jacobs et al (2004) asserts various physical processes associated with fog forecasting like humidification are not available in NWP models thus limiting the ways of visibility estimation. While testing the skill Mahringer (2008) concludes that it is wise to consider each variable at a time. The problem in testing the skill is assigning the score to different change groups such as BECMG, TEMPO and PROB used in the TAF; Mahringer (2008) asserts this, he further advices on the use of the highest observed value scoring for highest forecast value and worst observed value scoring for worst forecast value. When constructing an operational verification system most of the workload is spent on data management issues especially on data quality (Casati et al, 2008). As Terradellas (2007) concludes testing of skill will help mitigate inconveniences caused by poor visibility by increasing the accuracy and confidence placed on the forecast. The verification practice geared towards improvement of skill improves the confidence of the forecast. As Mason (2008) shows the verification scores should be used to answer the question, how good is the forecast and can we be confident that the forecast in not misleading. In assessing the skill for rare events Stephenson (2008) recommends a simple three parameter model for how hit rate and bias depends on base rate for vanishing rare event by forecasting on the extreme dependency score. The skill score are drawn from the contingency table since most events are binary. Forecast verification builds confidence placed on the forecast and also can be used as a tool for forecasting skill improvement and Ebert (2008) shows that from the forecast user perspective the fuzzy verification give important information on the scales and intensities at which the forecasts should be trusted. The forecast depends entirely on the forecaster's judgment of the situation leading to the hedging judgments which defines three related properties of verification measures which are propriety for forecasts in form of probability distributions and not deterministic distributions best fits the expectations for a single forecast. The next is the equitability for a series of forecasts and lastly the consistency measure (Jolliffe, 2008). The main aim of the forecast verification is ability to answer the questions how good is the forecast and what confidence is represented by a given forecast. Mason (2008) answers the question how good and confidence a forecast is by use of the confidence interval and further shows that the p-value cannot be applied for similar objective. Verification enables the deep insight into the forecast weaknesses and strengths with forecast geared towards methods for improving forecast quality hence management involvement is highly recommended as stressed by Stern (2008) the involvement of management will cascade the development and implementation of new prediction techniques and careful succession plan. The quality of the forecast and depends entirely on the quality of the observational data. The forecast verification is largely affected by the observation errors by reducing the apparent skill of the forecast (Bowler 2008), this can be rectified by applying fuzzy verification process (Ebert 2008) this relaxes requirements for exact matches between forecast and observations by using the spatial window or neighborhood surrounding the forecast and/or observed points. The problem of point forecast verification requires a large network of observing stations hence remains a challenge. Due to the problem of inadequate observing stations in and around Jomo Kenyatta International Airport the research will concentrate on the point verification.

CHAPTER THREE

3.0 DATA AND METHODOLOGY

This chapter presents the data and methods used to achieve the overall and specific objectives of this study.

3.1 DATA SOURCES

The data was obtained from the METARs and TAF forecasts obtained from the Jomo Kenyatta international airport meteorological office. A METAR is a meteorological aerodrome report if the observations are done at the aerodrome but if the observations are not done at the aerodrome but used for aviation operations then it becomes meteorological aviation report. The Terminal Aerodrome Report (TAF) is forecast used for aviation operation. The TAF comprises of forecast for wind speed and direction, visibility, weather and cloud amount and height of the base. Jomo Kenyatta International airport being an international airport the TAF cover thirty hours and is updated after every six hours. The data verified was for a period of one year beginning April 2012 till March 20113.

3.2 DATA QUALITY CONTROL

Data quality is very critical for inference testing. Most of the meteorological data errors arise at the point of observation. With the implementation of quality management in all meteorological aviation weather providers the quality of the data is guaranteed due to examination for completeness and consistency before transmission and storage for future use (ICAO Annex3).

3.3 DETERMINATION OF ACCURACY OF FORECAST

To determine the accuracy of forecast the forecasted value for visibility was checked alongside the observed value. Scatter plots for observations and forecasts were generated at both 0hr and 6hr lead times. In accuracy calculations, observation and forecast value indicated as 9999 was not considered since the actual value could not be determined, only specific determined values of forecast coinciding with the specific determined values observed were considered in accuracy calculations. The accuracy at 0hr and 6hr hour lead times was then calculated using the Root mean Square Error. The Root Mean Square Error formula is given below:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - O_i)^2}$$

3.4 SKILL ANALYSIS

The visibility was categorized into the following ranges:

a. Poor visibility between 0-1000m

b. Fair visibility between 1000 and 4000m

c. Clear visibility between 4000 and 9999m.

The ranges are defined basing on the thresholds related to flight operation. The category for poor represents the fog conditions which lowers the visibility to less than one kilometer. Occurrence of visibility value in the range indicated by poor may lead to diversions, holding, delays and flight cancellations, hence affecting the light schedule. The range indicated by fair shows obscurity to visibility such that the pilot intending to take off from the runway is not able to see the end of the runway, this can result in delays since plane separation on approach and landing is increased. The category with clear visibility does not lead to disruption of the schedule.

The contingency table can be used to draw conclusions about the forecast quality from the verification algorithm. It is the best way of evaluating the kind of errors being made by the forecaster. A perfect forecast would produce only the hits and correct negative events only.

The accuracy of the visibility forecast from TAF was checked alongside the observed visibility values from the METARs and based on the ranges discussed above a 3-category contingency table created as shown below

Table 1: Contingency table

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	a	b	C	**M**
	FAIR	d	e	F	**N**
	CLEAR	g	h	I	**O**
	TOTAL	**J**	**K**	**L**	**T**

A contingency table is essentially a display format used in the analysis of relationship between two or more categorical variable sand determining the forecasting skill by calculating various skill scores. Tartaglione (2010) describes a contingency table as a best way of testing the skill especially in weather forecasts. The forecasting technique depends entirely on the distribution of the observing stations and for good data validation as Roebber (2009) notes a good distribution of observing network is required in forecast verification. In this study the forecasts were verified with a lead time of zero and six hours.

From the contingency table the following skill score will be calculated

a) **Percentage Correct (PC)** – this score shows a fraction of the forecasts that is correct. It ranges from 0-1, with the perfect score being 1. This score can be misleading since it is heavily influenced by common category, usually no event in the case of rare events. It is determined by the formula

$$PC = \frac{a + e + i}{T} * 100$$

b) **Probability of detection/ hit rate (POD)** – POD shows the fraction of observed yes events that were correctly forecasted. The score ranges from 0-1, with score of 1being the perfect score. It is sensitive to hits but ignores false alarm making it good for rare events. The POD is determined by the following formula below

$$POD = \frac{a}{J}$$

c) **BIAS** – BIAS the forecast frequency of yes events compare to the observed frequency of yes events. The score ranges from 0 to ∞, with the perfect score being 1. The BIAS>1 and BIAS<1 indicates over-forecasting and under-forecasting respectively. BIAS measure ratio of the frequency of forecast events to the frequency of observed events. The skill score does not measure how well the forecast corresponds to the observations instead it measure only the relative frequencies. The skill score can be determined using the formula below

$$BIAS = \frac{M}{J}$$

d) **False Alarm Ratio (FAR)** – FAR shows the percentage of the predicted yes events that actually did not occur. The FAR skill score ranges from 0-1 with the perfect score being o. The skill score is sensitive to false alarms, but ignores misses. It is also very sensitive to the climatological frequency of the event. FAR skill score can be determined by applying the formula below

$$FAR = \frac{a + c}{M}$$

e) **Heidke skill score (HSS)** – HSS skill score indicates the accuracy of the forecast relative to that of random chance. HSS skill score ranges from -∞ to 1, with the perfect score being 1. The skill score measures the fraction of correct forecast after eliminating those forecasts which would be correct due purely to random chance. The HSS skill score can be determined by applying the formula below

$$HSS = \frac{a + e + i - \frac{JM + KN + LO}{T}}{T - \frac{JM + KN + LO}{T}}$$

f) **Pierces skill score/ Hanssen and Kuipers discriminant (HK)** – HK skill score shows how well the forecast separate the yes events from the no events. The score ranges from -1 to 1, with the perfect score being 1. The score does not depend on climatological event frequency. For rare events the score is unduly weighted hence more useful for more frequent events. This skill score is determined by the following formula

$$HK = \frac{a}{J} - \frac{b + c}{K + L}$$

g) **Critical success index /threat score (CSI/TS)** – CSI skill score shows how the forecast yes events corresponded to the observed yes events. The score ranges from 0-1, with the perfect score being 1. The score measures the fraction of observed and/or forecast events that were correctly forecasted. The score is sensitive to hits and penalizes both misses and false alarms. The score can be determined by the formula below

$$CSI \; or \; TS = \frac{a}{JM}$$

CHAPTER FOUR

4.0 RESULTS AND DISCUSSIONS

This chapter presents and discusses the results obtained from the methods described in chapter three to achieve the objectives outlined in section 1.3.

4.1 Temporal Distribution of Visibility Observations at Jomo Kenyatta International Airport

The temporal variability of visibility observed at Jomo Kenyatta International Airport was plotted using graphs as shown below

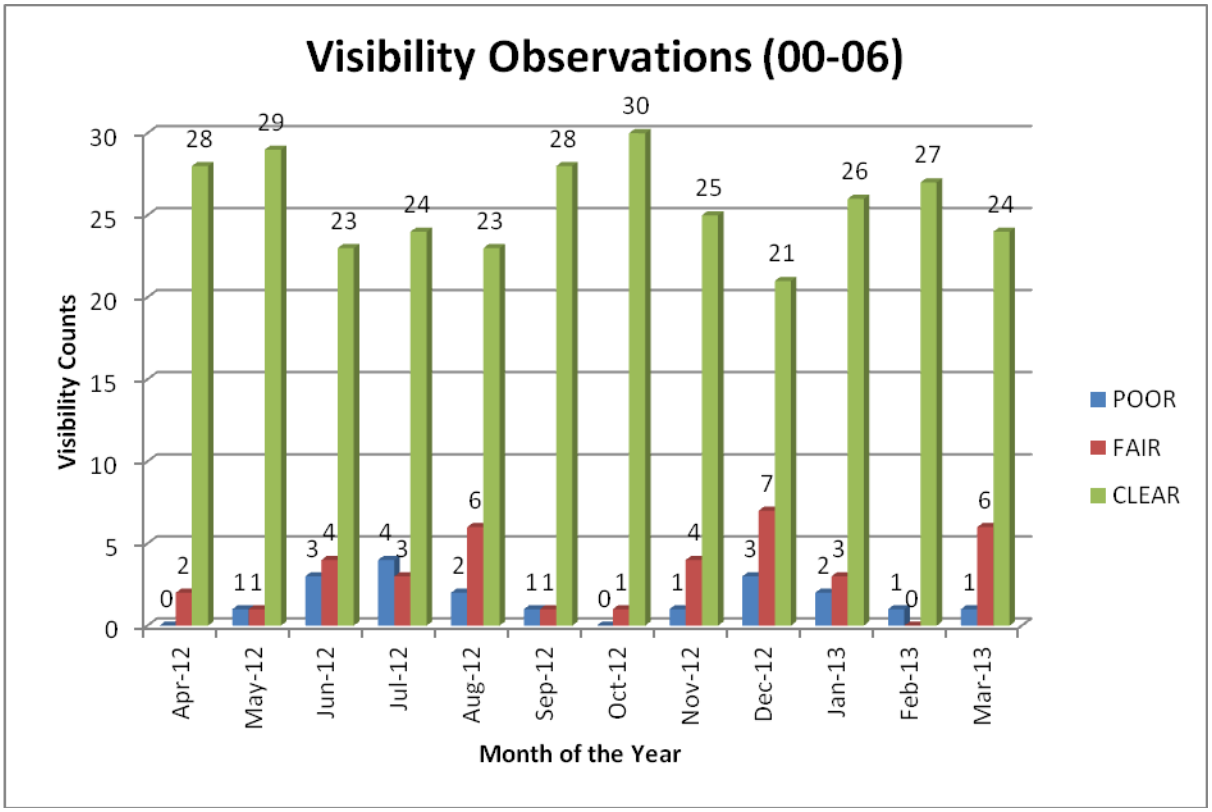

Figure 1: Visibility observations between 00Z and 06Z

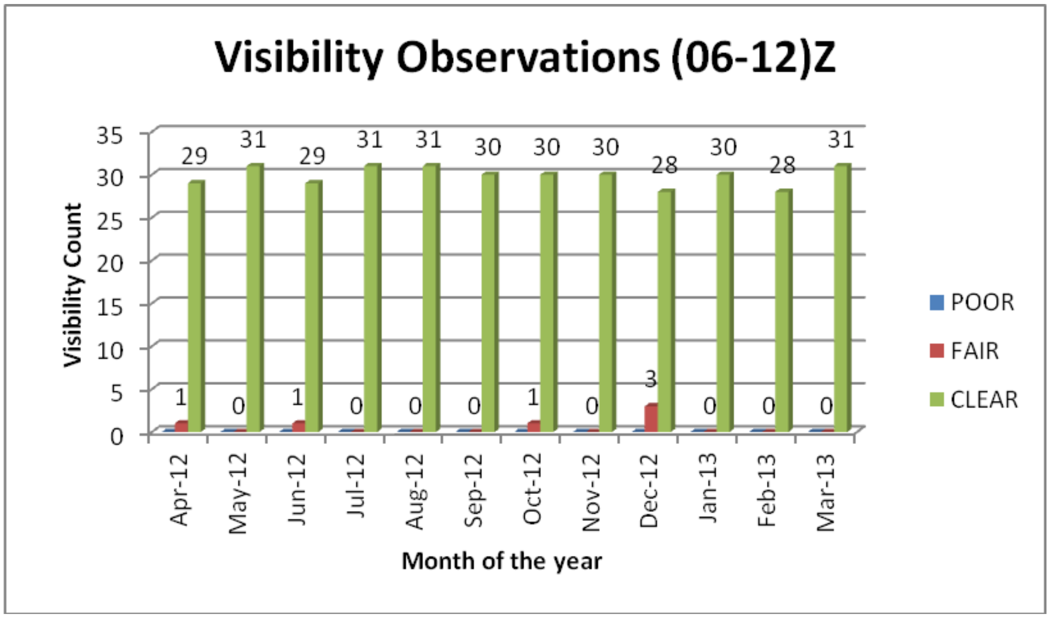

Figure 2: Visibility observations between 06Z and 12Z

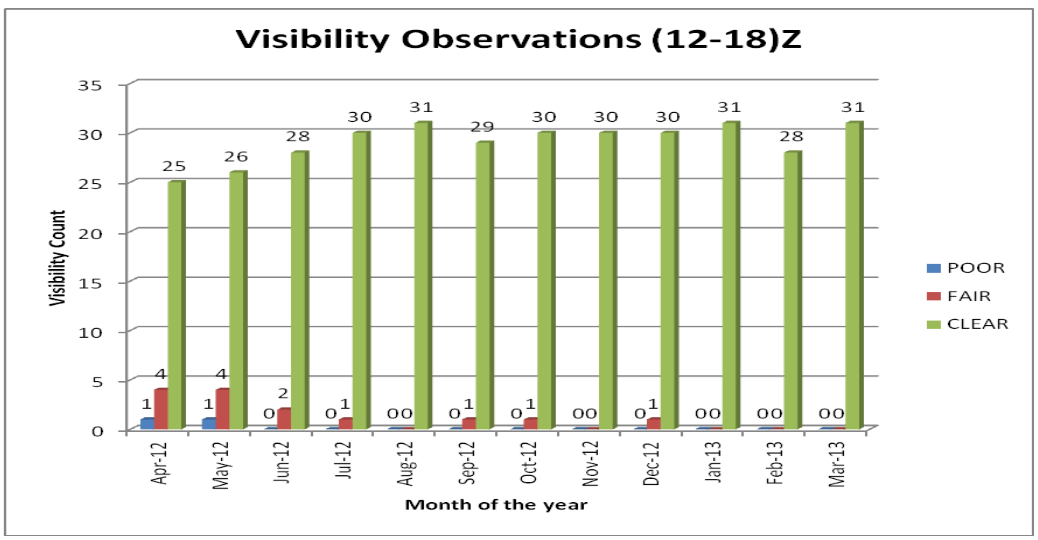

Figure 3: Visibility observations between 12Z and 18Z

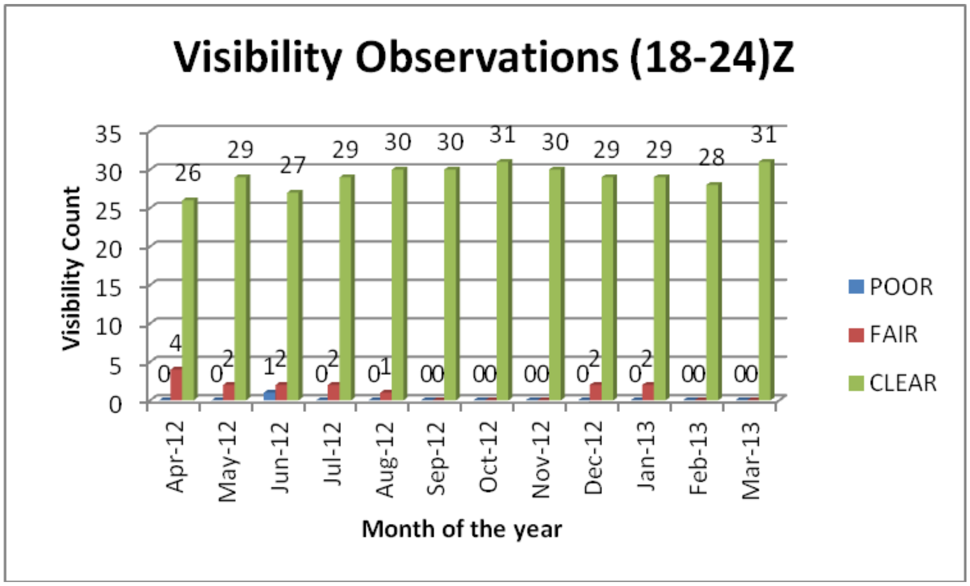

Figure 4: Visibility observations between 18Z and 24Z

From graphs the high frequency of poor visibility occurence was obsserved between 00Z and 06Z. The high frequency is attributed to fog occurence at the airport. The poor visibility is frequently observed during the months of June to August and again December to January. Poor visibility is again observed from 12Z to 18Z during the long rain season. The poor visibility during this period is brought about by heavy rainfall emanating from deep convective clouds.

4.2 Accuracy of visibility forecasts

The visibility forecast values and observed values were plotted on a scatter plot to show the relationship between the forecasted and the observed values. The scatter plot was generated for forecasts and observations between 0000Z and 0600Z since this is the range with many instances of poor visibility as shown in part 4.1 above. The graphs are shown below:

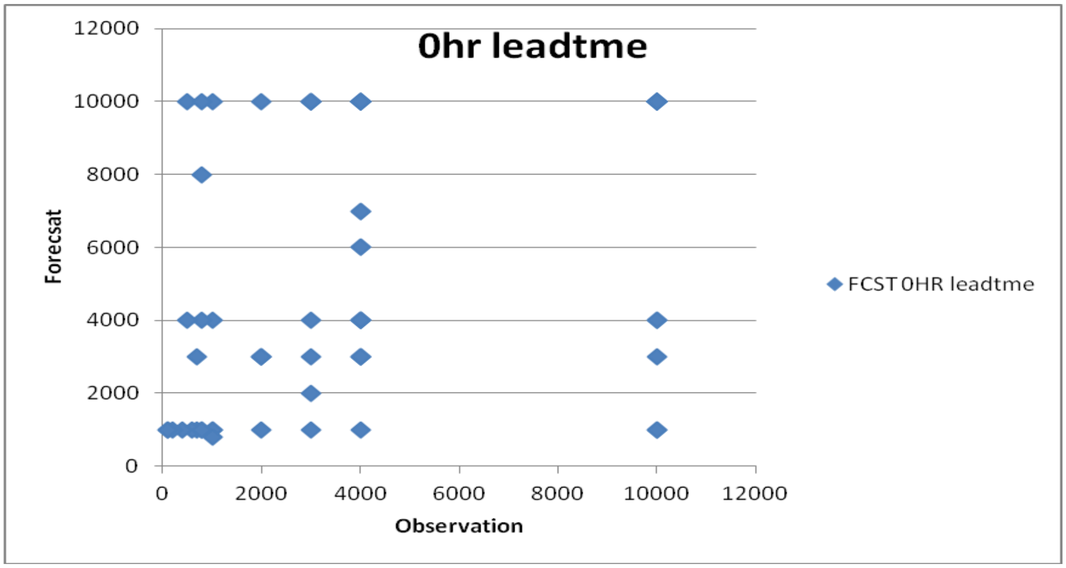

Figure 5: Scatter plot at 0hr lead time

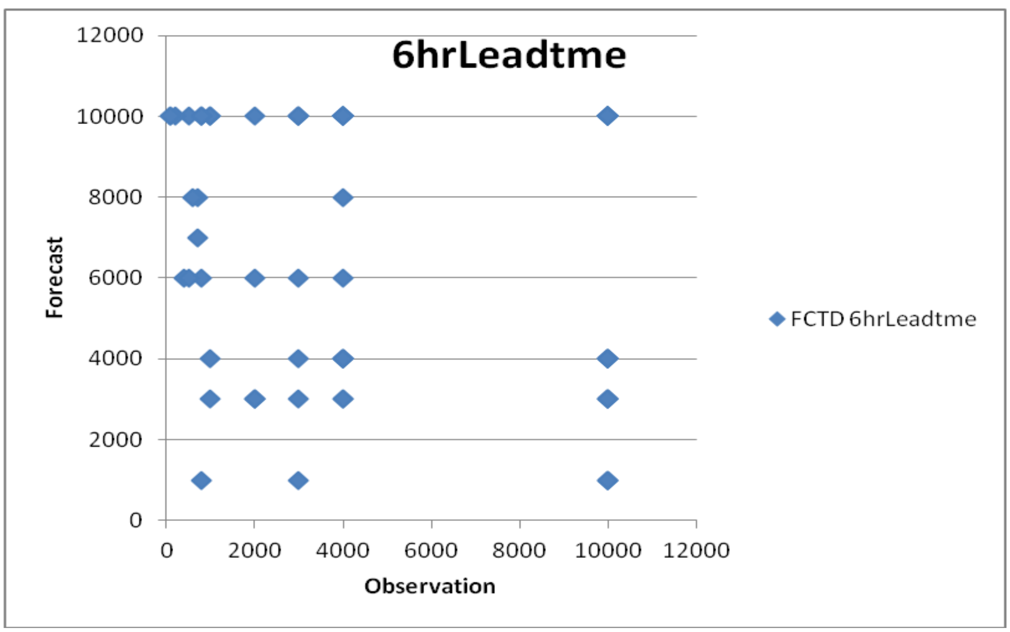

Figure 6: Scatter plot for 6hr lead time

From the scatter plots the higher margins represents the visibility of 9999 which indicates visibility of ten kilometers and above. The scatter plot for 0hr lead time shows that most of the cases visibility was correctly forecasted as compared that for 6hr lead time, implying that at 0hr lead time the forecasts were correct compared to the forecasts at 6hr lead time.

While calculating the accuracy of visibility forecasts, the observations and forecasts with visibility indicating 9999 were dropped from calculations since the actual value could not be determined. Only days with specific observed value coinciding with specific forecasted value were considered in this case. The accuracy calculations using the Root Mean Square Error was determined for 0hr and 6hr hour lead times respectively. The results are as shown in the table below

Table2: Root Mean Square Error

Lead time	RMSE
Zero hour	1.730
Six hour	4.414

The RMSE for a zero hour lead time is very low compared to the RMSE for a six hour lead time. From the results the visibility forecasts should be used just immediately after being produced by the forecast since they are more accurate as compared to the same forecast six hours after being produced by the forecast. From the results the visibility forecast accuracy deteriorates with increase in lead time. The accuracy deterioration could be due to the abrupt occurrence of phenomenon interfering with visibility and lack of adequate forecasting tools to forecast such phenomena.

4.3.0 Contingency Tables

By considering visibility forecast range discussed in methodology a 3- category contingency table was developed for zero and six hour lead time. The contingency tables were first categorized depending on the time of the day at which the forecasts were generated i.e 0000-0600, 0600-1200, and 1200-1800, and later a general contingency tables constructed for zero and six hour lead time incorporating the above time intervals.

4.3.1 Contingency tables analysis for 0000Z to 0600Z forecasts

The contingency table for forecasts generated at 0000Z were developed both for zero hour and six hour lead times as shown in the tables below:

Table 3: 0hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	11	3	2	**16**
	FAIR	4	13	3	**20**
	CLEAR	4	22	303	**329**
	TOTAL	**19**	**38**	**308**	**365**

Table 4: 6hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	1	1	3	**5**
	FAIR	1	13	19	**33**
	CLEAR	17	24	286	**327**
	TOTAL	**19**	**38**	**308**	**365**

The 0hr lead time shows higher number of correct forecasts for poor visibility as compared to forecasts at 6hr lead time. From the two tables skill scores were calculated for the two lead times as shown in the table and graphed as shown below

Table 5: Skill scores for 00Z-06Z forecasts

	0hr Lead time	6hr lead time
P.C	0.896	0.822
FAR	0.125	0.600
HSS	0.550	0.239
HK	0.564	0.041

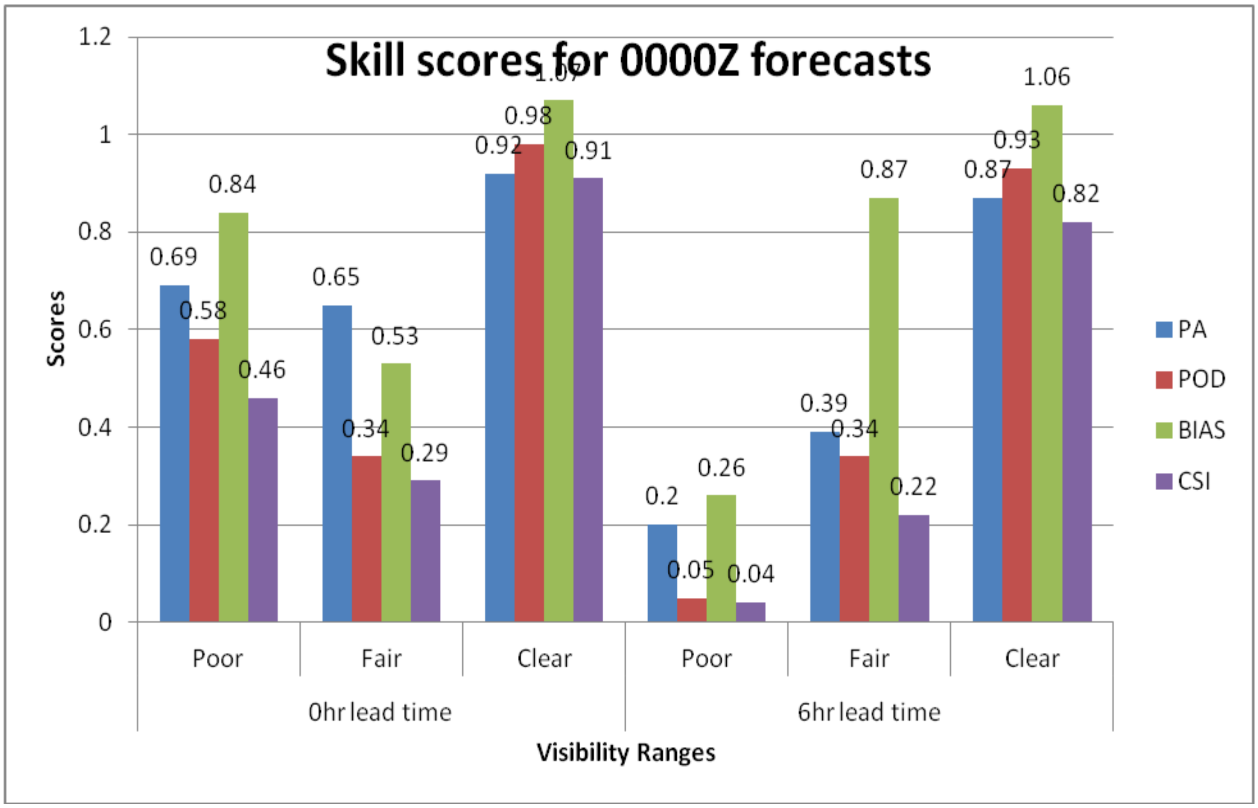

Figure 7: Forecast skill scores for 00Z to 06Z

From the results above, generally the scores are very high for 0hr lead time as compared to the 6hr lead time. The skill scores for poor visibility range were higher for 0hr lead time as compared to 6hr lead time. The skill scores for the clear range are very high since there is no technicality involved in forecasting clear visibility. In all the cases the probability of detection is very high due to high frequency of occurrence of clear weather. The FAR for 0hr lead time is much lower as compared the same at 6hr lead time.

4.3.2 Contingency tables analysis for 06Z-12Z, 12Z-18Z and 18Z-24Z forecasts

4.3.2.1 Contingency table analysis for 06Z-12Z

Table 6: 0hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	0	0	0	**0**
	FAIR	0	4	3	**7**
	CLEAR	0	2	356	**358**
	TOTAL	**0**	**6**	**359**	**365**

Table 7: 6hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	0	0	0	**0**
	FAIR	0	0	3	**3**
	CLEAR	0	6	356	**362**
	TOTAL	**0**	**6**	**359**	**365**

From the tables above, during the study period no instance of poor visibility was encountered either in the forecast or in observations between 06 and 12Z. However there were few instances of fair visibility which were correctly forecasted at 0hr lead time as compared to 6hr lead time.

4.3.2.2Contingency tables analysis for 1200Z-1800Z

Table 8: 0hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	1	0	0	**1**
	FAIR	0	8	1	**9**
	CLEAR	1	6	348	**355**
	TOTAL	**2**	**14**	**349**	**365**

Table 9: 6hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	0	0	0	**0**
	FAIR	0	0	0	**0**
	CLEAR	2	14	350	**365**
	TOTAL	**2**	**14**	**350**	**365**

From the tables above there were few instances of poor visibility with 0hr lead time showing hits while at 6hr lead time the same was missed. The instances of fair visibility from the tables above could only be correctly forecasted at 0hr lead time.

4.3.2.3 Contingency tables analysis for 1800Z-2400Z

Table 10: 0hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	0	0	0	**0**
	FAIR	0	7	0	**7**
	CLEAR	1	7	350	**358**
	TOTAL	**1**	**14**	**350**	**365**

Table 11: 6hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	0	0	0	**0**
	FAIR	0	0	0	**0**
	CLEAR	1	14	350	**365**
	TOTAL	**1**	**14**	**350**	**365**

From the above contingency tables the occurrence of poor visibility is very low thus increasing the number of correct forecast due to high frequency of clear weather which is much easier to forecast through persistency. The percentage correct for each table is given in the table below

Table 12: Percentage correct for 06-12Z, 12-18Z, and 18-24Z forecasts

Time	0hr lead time	6hr lead time
0600-1200	0.9863	0.9753
1200-1800	0.9781	0.9562
1800-2400	0.9781	0.9587

Although the score are higher both for zero hour and six hour lead time, zero hour lead time shows a higher percentage correct as compared to the six hour lead time. This is due to the fact that there were more correct forecasts for 0 hr lead time than for 6 hr lead time.

4.3.2.4 Generalized contingency table analysis

Table 13: 0 hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	12	3	2	**17**
	FAIR	4	32	7	**43**
	CLEAR	6	37	1357	**1400**
	TOTAL	**22**	**72**	**1366**	**1460**

Table 14: 6 hr lead time

		OBSERVED			
		POOR	**FAIR**	**CLEAR**	**TOTAL**
FORECAST	**POOR**	1	1	3	**5**
	FAIR	1	13	22	**36**
	CLEAR	20	58	1341	**1419**
	TOTAL	**22**	**72**	**1366**	**1460**

From the tables the number of correct forecasts at 0 hr lead time is higher as compared to the same at 6 hr lead time. The instances of poor visibility were in most instances correctly forecasted at 0 hr lead time than at 6 hr lead time. From the generalized contingency tables the following skill score were calculated and represented in the graph and table below.

Table 15: Skill scores from generalized contingency table

	0hr Lead time	**6hr lead time**
P.C	0.9596	0.9281
FAR	0.2941	0.80
HSS	0.60	0.20
HK	0.54	0.04

From the table the skill score are very high for the 0hr lead time as compared to the 6hr lead time. The 0hr lead time shows a low FAR as compared to the 6hr lead time which high. There were more correct forecasts at 0 hr lead time than at 6 hr lead time hence the higher score for P.C, HSS and HK and lower scores for FAR.

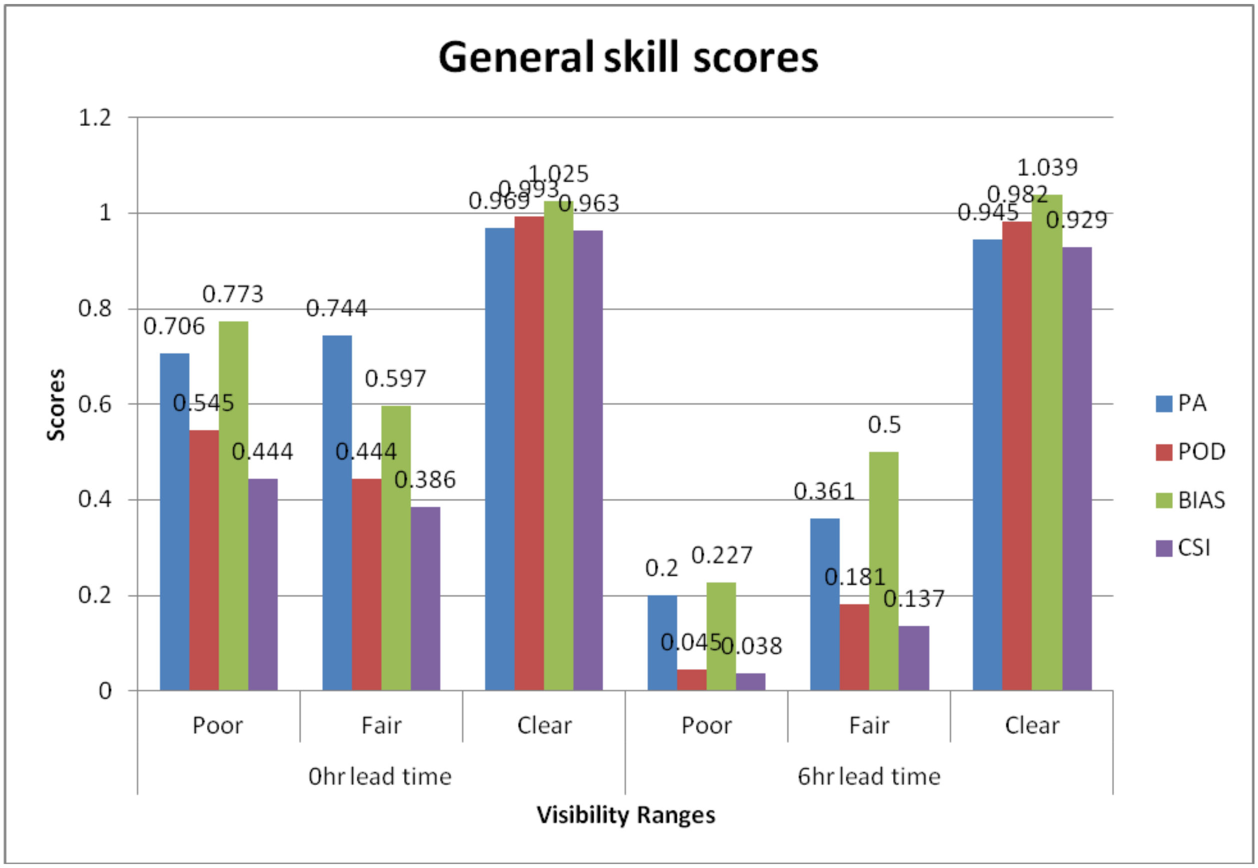

Figure 8: General forecasting skill scores

From the graph above the skill scores like P.C, HSS, HK, PA, POD and CSI related to 0 hr lead time are higher as compared to the same for 6 hr lead time. The FAR at 0 hr lead time is lower as compared to that for 6 hr lead time. The scores related to instances of poor visibility are lower as opposed to those with clear visibility; this is an indication that the forecasters are challenged when it comes to forecasting visibility interference as opposed to forecasting clear visibility instances. It is easier to forecast clear visibility through persistence evidenced by high scores for clear visibility forecasts. The number of correct forecasts at 0 hr lead time is higher as compared to the same at 6 hr lead time.

CHAPTER FIVE

5.0 SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

This chapter presents the study summary, main conclusions and recommendations for further study have also been suggested.

5.1 Summary of the study

The main objective of this study was to verify the visibility forecasts generated at Jomo Kenyatta International Airport, so as to ascertain accuracy and forecasting skill. The data for the study was obtained from METARs and TAFs generated at Jomo Kenyatta International Airport for a period running from April 2012 till March 2013. Visibility was categorized into three ranges poor, fair and clear visibility ranges. The forecast and observed values were compared to determine the accuracy by using scatter plot and the root mean square error method for 0hr and 6hr lead times. Visibility forecasts were checked alongside visibility observations considering 0hr and 6hr lead times. A 3-category contingency table was developed for each lead time and analyzed for skill scores. Both the accuracy and skill for visibility forecast was found to be high for 0hr lead time as opposed to 6hr lead time.

5.2 Conclusions of the study

The visibility forecast contained in the TAF contains a range of forecast rather than a single state. This is specifically achieved by use of change groups like TEMPO, BECMG and PROB. These change groups are not considered while carrying out verification in this study. To determine the accuracy for 0hr and 6hr lead times, METAR s corresponding to the forecast period were checked alongside the forecast for visibility and root mean square error determined for forecast coinciding with observed values which could be determined. Visibility was divided into three threshold ranges i.e. poor, fair and clear and a 3-category contingency table general from which the skill scores were calculated. From analysis both accuracy and skill scores were higher when the 0hr lead time was considered, but with 6hr lead time the accuracy and skill had dropped drastically. From the analysis the visibility forecast should be utilized immediately after their production and amendments and updates to the forecast should be considered with utmost urgency for flight operations. The ICAO requires that each TAF should be updated after every six hours for 24hr and 30hr TAFs and amendments issued promptly whenever need arises, this need is evidenced from the results since the accuracy and skill drastically falls after six hours.

5.3 Recommendations

TAF provides forecast for wind speed and direction visibility, weather and ceiling conditions. Apart from fog, precipitation, smoke and sand dust, ceiling can significantly affect the visibility especially when vertical visibility is considered. This study concentrated only on verification of visibility forecast however all the parameters covered in the TAF should be verified separately to determine accuracy and skill of the forecast. Verification of the Take-off and landing forecasts is recommended to establish the accuracy and skill for each forecast since this will go a long way in judgmental decision making in the aviation operations.

The accuracy and skill at 0hr lead time is very high thus recommended for use in flight planning, but it drastically falls for the six hour lead time. To address the drop the management should consider improvement of the equipment for observing and forecasting visibility at the airport since it was noted that the RVR boards are not functional at Jomo Kenyatta international airport and the radar is also not in use. The forecasters should be considered for training in long range poor visibility forecasting so as to improve the accuracy and skill for 6hr lead time.

The verification results should be presented to customers and feedback obtained from the customers. This will assist in determine the value of aviation weather forecasts to the customers.

REFERENCES

Benedetti R (2010). Scoring Rules for Forecast Verification. *Monthly review*. Vol. 138:203-211

Casati B., Wilson J. L., Stephenson B. D., Nurmi P., Ghelli A., Pocernich M., Damrath U., Ebert E. E., Brown G. B., and Mason S.(2008). Forecast verification: current status and future directions. *Meteorological applications*. Vol.15: 3-18.

Ebert E. E. (2008). Fuzzy verification of high resolution gridded forecasts: a review and proposed framework. *Meteorological applications.* Vol 15: 51-64.

Fabbian D Dear R and Lellyett S, (2007). Application of Artificial Neural Network Forecasts to Predict Fog at Canberra International Airport. *Weather and forecasting.* Vol. 22: 372-381

Goteman O, Smith K and Dekker S (2007). HUD with a Velocity (Flight-Path) Vector Reduces Lateral Error During Landing in Restricted Visibility. *The International journal of aviation psychology*. Vol. 17: 92-108

Gultepe I, Tardif R, Michaelides S.C, Cermak J, Bolt A, Miller M. D, Bendix J, Pagowski M, Hansen B, Ellrod G, Jacobs W, Toth G, Cober S. G, (2007). Fog Research: A review of Past Achievements and Future Perspectives. *Pure and applied geophysics*. Vol. 164, pp 1121-1159.

ICAO (2010). Annex 3, Meteorological Service for International Air Navigation

Jacobs A. J. M. and Maat N. (2004). Numerical Guidance Methods for Decision Support in Aviation Meteorological Forecasting. *Weather and forecasting.* Vol. 20:82-100

Jenamani R. K and Tyag A (2011). Monitoring Fog at IGI Airport and Analysis of its Runway-wise Spatio-temporal Variations Using Meso-RVR Network. *Current science.* Vol. 100:491-501

Jolliffe T. I., (2008). The impenetrable hedge: a note on propriety, equitability and consistency. *Meteorological applications.* Vol 15: 25-29.

Kramer J L, Bauley E R, and Prinze J L, (2008). Commercial Flight Crew Decision Making During Low Visibility Approach Operations Using Fused Synthetic & Enhanced Vision Systems. *International Journal of Aviation Psychology*. Vol 19 No. 2 pp 131-157

Lehman R (1987). Probability Distribution of Monthly Degree Day Variables at U.S Station. Part 1: Estimating the Mean Value & Variance from Temperature Data. Journal of Climate & Applied Meteorology. Vol. 26. Pp 329-340

Mahringer G (2008). Terminal Aerodrome Forecast Verification in Austro Control Using the Windows & Ranges of Forecast Conditions. *Meteorological applications.* Vol. 15: 113-123

Mason S. J (2008). Understanding Forecast Verification Statistics. *Meteorological applications.* Vol. 15: 31-40

McDonald E. J (1962). Visibility Reduction Due to Jet-Exhaust Carbon Particles. Journal of Applied Meteorology. Vol. 1 pp 391-398

Muiruri S (2006). Influence of Fog on Aircraft Operations at Jomo International Airport, Post Graduate Diploma in Aviation Meteorology Research Project.

Muiruri S (2011). Assessment of Adverse Weather on the Operation of Air Transport at Jomo Kenyatta International Airport and Wilson Airport. Masters of Science in Aviation Meteorology.

Naegele P. S & Sellers D. W (1981). A Study of Visibility in Eighteen Cities in the Western & South-Western United States. Monthly Weather Review. Vol. 109 pp 2394-2400

Patterson E. M Gillette A. D & Grams W. G (1976). The Relation Between Visibility & the Distribution of Airborne Soil Particles. Journal of Applied Meteorology. Vol.15 470-478

Reynolds W. D Clark A. D Wesley W F & Cook L (2012). Forecast-based Decision Support for San Francisco International Airport. A NextGen Prototype System that Improves Operations During Summer Stratus Season. *Bull. Amer. Meteor. Soc.* Vol.93 1503-1518

Roebber P. J (2009). Visualizing Multiple Measures of Forecast Quality. *Journal of Applied meteorology and climatology.* Vol. 47: 601-608.

Roquelaure S and Bergot T (2008). A Local Ensemble Prediction System for Fog and Low Clouds: Construction, Bayesian Model Averaging Calibration & Validation. *Journal of Applied Meteorology & Climatology*. Vol. 47:3072-3088

Ruddack E. D & Ghirardelli E. J (2010). A comparative Verification of Localized Aviation Model Output Statistics Program (LAMP) & Numerical Weather Prediction (NWP) Model Forecasts of Ceiling Height & Visibility. *Weather & forecasting.* Vol. 25: 1161-1178

Stephenson B. D., Casati B., Ferro T. A. C., and Wilson A.C. (2008). The extreme dependency score: a non-vanishing measure for forecast of rare events. *Meteorological applications.* Vol 15: 41-50.

Stern H. (2008). The accuracy of weather forecasts for Melbourne, Australia. *Meteorological applications.* Vol 15: 65-71.

Tartaglione N (2010). Relationship Between Precipitation Forecast Errors and Skill Scores of Dichotomous Forecasts. *Weather & forecasting.* Vol. 25: 355-365

Terradellas E & Cano D. (2007). Implementation of a Single-Column Model for Fog and Low Cloud Forecasting at Central-Spanish Airports. *Pure and applied geophysics.* Vol. 164: 1327-1345

Tjerntrom M (1993). Simulated Liquid Water and Visibility in Stratiform Boundary-Layer Clouds over Sloping Terrain. *J. Appl. Meteor.* Vol. 32 pp 656-665