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MACROSCOPIC MODELING OF THE IMPACTS OF THE STANDARD GAUGE RAILWAY LINE ON THE PERFORMANCE OF THE NORTHERN ROAD TRANSPORT CORRIDOR

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Abstract: With a predicted rapid international and regional trade within the region, the Northern road transport corridor will have to deal with the challenges associated with additional traffic growth without compromising on travel time, safety and environmental concerns. Towards this, the Kenyan government embarked on the construction of the Standard Gauge Railway Line (SGRL) in order to improve the Northern Corridor network performance so as to enhance the logistics competitiveness along the corridor. The paper presents the findings of an ongoing research into the impacts of freight traffic on roadway capacity related elements such as travel time, speed, volume to capacity ratios as well as ozone emissions on the corridor. Under the plausible economic growth regime, the SGRL will only divert a maximum of 20% of freight demand from the road network and is expected to reduce capacity on the network, reduce travel time, minimize emissions concentrations and improve the entire network reliability. However, this will depend on the rail modal split capacity, and as such the excess capacity will only be handled by the road network which in turn will result into capacity constraints beyond the 2025. Further, the SGRL will result in substantial reduction of Ozone concentration along the network up to the forecast year 2020 only, beyond which the Ozone concentration on some sections of the corridor will begin to exceed the acceptable WHO standards of 100µg/m^3.

Keywords: *Impacts of freight, macro-scopic modelling, travel time, speed, volume to capacity ratio and emissions*.

1.0 Introduction

The Northern road transport corridor (Figure 1) is the key freight transport corridor that connects the port of Mombasa to markets in Kenya and other land-locked countries of Uganda, Rwanda, Burundi and Democratic Republic of Congo, as well as Southern Sudan, Northern Tanzania and Ethiopia. With a predicted rapid international and regional trade and the growth in GDP within the region, the corridor will have to deal with the challenges associated with additional traffic growth without compromising on

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the travel time, safety and environmental concerns. It is against this backdrop that the research intended to develop a robust macro-scopic freight travel forecasting model capable of estimating the impacts of freight traffic on the performance of the Northern road transport corridor using PTV VISUM transportation planning software. The study focused on evaluating the impacts of freight on capacity related impacts such as speed, delay, travel time, volume to capacity ratios as well as emissions. A 20-year forecast model has been developed with 2015 as the base year, with a spatial coverage of the Kenyan portion of the corridor.

Figure 1: The Northern Transport Corridor

2.0 Freight Model Development Approach

2.1 Stages

The development of the Northern transport corridor freight model adopted the conventional approach to travel demand forecasting and comprised of the following main stages:

1. Stage 1 – Forecasts of trade and freight traffic demands
2. Stage 2 - Development of a VISUM platform for the Northern Corridor transport network to integrate the supply and demand components of the model
3. Stage 3 – Calibration and Northern Corridor transport network scenario testing

2.2 *Historical Trade and Traffic Data*

Freight demand is created and governed by demographic and economic activities. The demographic and economic model adopted for the research was based on a top-down approach to forecast both population and real GDP growth for Kenya from 2015 to 2030. The forecasts of population and GDP growth for Kenya has been done in a theoretically consistent fashion from publicly available data sources including the Kenya National Bureau of Statistics (KNBS) and the World Bank with the main assumption that the Kenya's economic output follows the growth profile set out in the Economic Vision 2030 report. A review of historic trade data and traffic flows along the corridor was done in order to provide a reference point for future forecasts. The historical trade presented as imports and exports over the past decade is provided in Table 1 while Table 2 presents container traffic data in Twenty Foot Equivalent Units (TEU's) along the corridor over same period.

Table 1: Historical Trade along the Corridor

Type of Cargo ('000'DWT)	Year									
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Imports Dry	4005	3918	4841	5423	5782	6443	7588	7870	10076	9815
Exports Dry	1803	2171	1723	2248	2105	2123	2307	2495	2283	2480
Liquid Bulk	4490	4135	4762	4841	5091	5535	5641	5631	6598	6481
Total	10298	10224	11326	12512	12978	14101	15536	15996	18957	18776
Transshipment	303	340	605	409	303	318	426	419	105	158
Total	10601	10564	11931	12921	13281	14419	15962	16415	19062	18934

Source: Kenya Ports Authority (KPA)

Table 2: Historical Container Traffic (TUE's) along the Corridor

Container Traffic ('000' TEU's)	Year									
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Imports	134.5	143.4	173.5	203.9	207.8	229.5	282.0	297.4	307.8	345.3
Exports	130.2	134.7	157.2	200.4	201.6	218.6	266.9	283.9	301.5	335.7
Transshipment /Empties	257.7	27.4	49.6	34.2	27.3	31.3	36.5	34.5	9.5	14.6
Total	290.5	305.4	380.3	438.6	436.7	479.4	585.4	615.7	618.8	695.6

Source: Kenya Ports Authority (KPA)

2.3 *GDP Forecasting*

Vector Auto-Regression (VAR) model was adopted for forecasting GDP growth in this research Ben-Akiva *et al.* (2013); Andersson (2007); Robertson & Tallman, (1999) and Bergheim (2008). In this approach, forecasts are made one-step-ahead (horizon *t+1)* and iterates forward. The first forecast for t+1 is based on the primary estimated parameters and the information available at time t. Then the updated estimated parameters are used to make one-step-ahead forecasts for the desired number of periods, until $t+h$. A one step horizon (t+1) show that the forecast is made for one quarter ahead. Forecasts in this research are performed for horizons up to t+16 ahead. Similar to Marcellino, Stock and Watson (2005), a three variable VAR model is used with GDP, unemployment and inflation as variables. A reduced VAR model expressed as a linear function is presented as follows Andersson (2007);

$$GDP_{1t} = \propto + \beta_1 GDP_{t-1} + \beta_2 GDP_{t-2} + \cdots + \beta_j GDP_{t-j} + \gamma_1 HICP_{t-1} + \gamma_2 HICP_{t-2} + \cdots + \gamma_j HICP_{t-j} + \delta_1 UN_{t-2} + \cdots + \delta_j UN_{t-j} + \mu_t \quad (1)$$

Which implies that;

$$GDP_{1t} = \propto + \sum_{j=1}^{k} \beta_j \, GDP_{t-j} + \sum_{j=1}^{k} \gamma_j HICP_{t-j} \sum_{j=1}^{k} \delta_j \, UN_{t-j} + \mu_t \quad (2)$$

Where GDP at time t depends on past values of the explanatory variables GDP, inflation and unemployment up to a lag length of k, $\propto$ is a constant term, μ_t is the stochastic error term, k is the number of lags selected. β,γ and δ are coefficients that represent the individual contributions of the independent variables to the prediction of the dependent variable; j is the notation, in this case it means that the series starts from j and ends in k. The input parameters of the model are presented in the Table 3:

Table 3: GDP Forecasting Input Parameters

Year	GDP	Inflation	Unemployment
2000	0.6	9.98	17.3
2001	4.4	5.74	17.0
2002	0.4	1.96	17.2
2003	2.8	9.82	17.1
2004	4.3	11.62	17.0
2005	5.9	10.31	16.9
2006	6.3	14.45	16.9
2007	7.0	9.76	17.2
2008	1.6	26.24	17.2
2009	2.6	9.23	17.1
2010	5.8	3.39	16.9
2011	6.1	14.02	17.0
2012	4.6	9.4	17.0
2013	5.7	5.7	17.1
2014	5.3	6.9	18.2

Source: Kenya National Bureau of Statistics

Using Equations 1 and 2 above, with the above input variables, the GDP forecasts for the year 2015 to 2030 including the KNBS and World Bank forecasts is provided in Table 4.

Table 4: GDP Model Forecasts and Sensitivity

Year	Model Forecast	KNBS Forecast	World Bank Forecast
2015	6.36	6.54	6.02
2016	6.69	6.72	6.61
2017	6.61	6.73	6.52
2018	7.24	7.54	7.43
2019	7.18	7.21	7.01
2020	7.07	7.21	6.91
2021	6.97	6.90	6.81
2022	6.94	6.84	6.71
2023	6.72	6.67	6.61
2024	6.59	6.66	6.52
2025	6.54	6.65	6.43
2026	6.49	6.42	6.34
2027	6.32	6.36	6.25
2028	6.38	6.43	6.16
2029	6.24	6.17	6.08
2030	6.27	6.21	6.00

The results of the model forecasts were within acceptable margins of error (calculated R^2 value of 0.9278) when compared with the KNBS and World Bank forecasts.

2.4 Population Forecasts

Population forecasts was accomplished using present and past population records obtained from the census data of KNBS. The methodology adopted in this research is the incremental increase method which is a modification of arithmetical increase method (Brockwell and Davis (2002) presented as:

$$P_n = P + n * X + \left\{\frac{n(n+1)}{2}\right\} * Y \quad (3)$$

Where,
Pn= Population after nth decade
X = Average increase
Y = Incremental increase

Using equation 3, the population forecast for the year 2010 to 2030 is provided in Table 5. These growth forecasts are reasonable and fit within acceptable margins of error with the calculated R^2 value of 0.9944 when compared with the KNBS and the World Bank forecasts.

Table 5: Population Model Forecasts and Sensitivity

Population Forecast	Actual*					Forecast				
	1969	1979	1989	1999	2009	2010	2015	2020	2025	2030
KNBS	10.9	15.3	21.4	28.7	38.6	39.82	46.45	52.60	58.62	65.90
Model	-	-	-	-	-	40.21	46.53	52.42	59.27	66.42
World Bank	13.19	15.66	22.67	30.48	38.82	40.91	46.75	52.9	59.39	66.31

*obtained from KNBS and the World Bank

Two economic and population scenarios have been modeled to incorporate the downside risks and upside opportunities associated with global recession, sovereign debts recovery, fluctuation in global oil prices among others. While there is no clear methodology to quantify the risks and/or upsides for this study, it was assumed that the high and low scenarios will utilize the factor of ±10% relative to the base model forecast scenario.

2.5 Trade Flow Forecasts

A two stage least squares regression analysis (2SLS) was carried out for forecasting trade flows model the relationship between trade flows, GDP and population as specified below (Krugman and Obstfeld, 2006; Ben-Akiva *et al.*, 2013):

$$\frac{\Delta AVT_{id}}{AVT_{ido}} = k_{id}\left(\frac{\Delta Y_i}{Y_{io}}\right)^{\alpha d}\left(\frac{\Delta P_i}{P_{io}}\right)^{\beta d} \quad (4)$$

Where:

AVT_{id} = Adjusted value of trade for country i and direction d (import or export) in year 0
AVT_{ido} = Adjusted value of trade for country i and direction d (import or export) in year 0
Y_{io}= GDP for country i in year 0
P_{io} = Population for country i in year 0
k_{id} = constant (residual annual growth rate) derived from calibration
αd = exponent of GDP derived from calibration for direction *d*
βd = exponent of population derived from calibration for direction *d*

The trade forecasts were based on three key steps:

i. The determination of past trade flow values as contained in the United Nation commodity trade statistics (COMTRADE) data base;
ii. The forecasts of GDP as described in the previous section;
iii. The forecasts of population growth as highlighted in the previous section;
iv. Modeling of the relationship between trade volume, GDP and population; and
v. Forecasting of the volumes for imports and exports

Trade value growth was analyzed from 2000 to 2010 through the creation of database queries on the COMTRADE database for the total imports and total exports. In this formulation the exponents for GDP and population growth were obtained as elasticities of trade with respect to GDP and population. A second stage estimation was carried out to determine the residual annual growth rate for Kenya as provided in Table 6.

Table 6: Model Calibration Values

Elasticities	Imports	Exports
Elasticity of GDP ($\epsilon 1$)	+0.175	+0.253
Elasticity of population ($\epsilon 2$)	+0.358	+0.798
Annual residual growth rate	3.14%	2.93%

In order to adjust the model for trade volume forecasts, the elasticity with respect to GDP was adjusted based on the change in value to volume ($\epsilon 3 = \epsilon 1 * f_i$) where f_i is the adjustment factor for change in value to volume over the calibration period of the model (2000 to 2010). This corrects for the underestimation of the effect of GDP on the volume of trade due to the calibration on trade values. The trade flow model adopted a time series Auto Regressive Integrated Moving Average (ARIMA) model using population and GDP to project the imports and exports of traded commodities from 2010 until 2030 as presented in the below equations Robertson & Tallman (1999):

For imports:

$$M_{in} = M_{i2010}\, FV_{min}\, (1+g_{im})^n \left(1+\frac{\epsilon 3m * \Delta Y_{in}}{Y_{i2010}}\right)\left(1+\frac{\epsilon 2m * \Delta P_{in}}{P_{i2010}}\right) \tag{5}$$

For exports:

$$X_{in} = X_{i2010}\, FV_{xin}\, (1+g_{ix})^n \left(1+\frac{\epsilon 3x * \Delta Y_{in}}{Y_{i2010}}\right)\left(1+\frac{\epsilon 2x * \Delta P_{in}}{P_{i2010}}\right) \tag{6}$$

Where:
M_{in}= the volume of imports forecast for year n
X_{in}= the volume of exports forecast for year n

M_{i2010} = the volume of imports in year 2010 (value of imports / ratio of value to volume for non-resource-based imports in 2010)
X_{i2010} = the volume of exports in year 2010 (value of exports / ratio of value to volume for non-resource-based exports in 2010)
FV_{min} = the factor for future change in average value to volume of non-resource-based imports for country i by year n
FV_{xin} = the factor for future change in average value to volume of non-resource-based exports for country i by year n
g_{im} = the annual residual growth rate for imports
g_{ix} = the annual residual growth rate for exports
Y_{i2010} = GDP for country i in year 2010
ΔY_{in} = change in GDP for country i from 2010 to forecast year n
P_{i2010} = population for the year 2010
ΔP_{in} = change in population for country i from 2010 to forecast year n

Utilizing the above equations with GDP and population values as variables, the resulting import and export forecast tonnages for the base case scenario is presented in Table 7.

Table 7: Import and Export Trade Volume Forecasts (000 tonnes)

Year	2010	2011	2012	2013	2014	2015	2020	2025	2030
Imports	16632	16874	18756	19921	21567	22971	32582	42765	48736
Exports	1854	2173	2048	2242	2654	3367	5722	6692	7621

The model forecast values were compared with other trade flow forecasts for the port of Mombasa in order to determine the reasonableness of the model results. The results are very sensitive and follow similar trends to the United Nations Commodity flow and the Kenya Ports Authority's actual and forecasted values with a coefficient of determination values of 0.87 and 0.94 respectively. The resulting basecase imports and exports values formed the demand input values in the VISUM freight travel demand forecasting model.

3.0 Visum Freight Modeling Platform

3.1 Introduction

PTV VISUM software was employed as the modeling platform. In general, the Northern transport corridor freight model can be summarized as an input-based four-step process comprising of trip generation, distribution, modal split and trip assignment. The model utilized a single-level zoning structure to make appropriate use of freight-related data to reflect the origins and destinations of freight traffic. These included 11 zones segmented and demarcated based on major geographic constraints that can easily be linked to population, GDP and other socio-economic data. As shown in Figure 2, the Freight Analysis Zones (FAZ) included; Mombasa, Athi River, Nairobi, Naivasha, Kericho, Eldoret, Malaba, Kisumu, Kisii, Isebania and Busia.

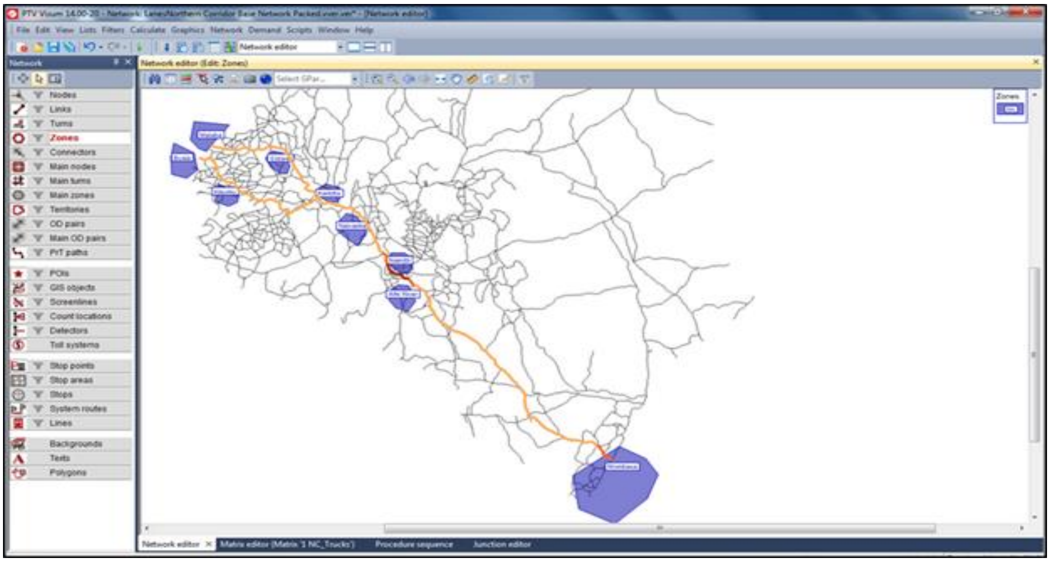


Figure 2: The Northern Corridor base Model Network and Zones

3.2 Trip Distribution

The formulation of the conversion from commodity tonnes to equivalent number of trucks was adopted from the FHWA (2007) methodologies and involved five main steps as highlighted below:

1. identifying the primary truck configurations and major truck body types;
2. allocating commodities to truck body types that are used to transport these commodities;
3. estimating average payloads by vehicle group and body type; and
4. converting the commodity tonnes into the equivalent number of trucks, with an additional step involving an estimation of the percent of empty truck trips.

The number of trucks of type ($Y_{j=1}$) used to move ($X_i\beta_{ijk}$) tons of commodity (X_i) by all body types is given by:

$$Y_{j=1} = \frac{X_i\beta_{i11}}{\omega_{i11}} + \frac{X_i\beta_{i12}}{\omega_{i12}} + \frac{X_i\beta_{i13}}{\omega_{i13}} + \cdots . + \frac{X_i\beta_{i19}}{\omega_{i19}} = \sum_{k=1}^{k=9} \frac{X_i\beta_{i1k}}{\omega_{i1k}} \quad (7)$$

Similarly, the number of trucks of type (Y_j=2) used to move ($X_i\beta_{ijk}$) tons of commodity (X_i) by all body types is given by:

$$Y_{j=2} = \frac{X_i\beta_{i21}}{\omega_{i21}} + \frac{X_i\beta_{i22}}{\omega_{i22}} + \frac{X_i\beta_{i23}}{\omega_{i23}} + \cdots . + \frac{X_i\beta_{i29}}{\omega_{i29}} = \sum_{k=1}^{k=9} \frac{X_i\beta_{i2k}}{\omega_{i2k}} \tag{8}$$

Thus, the number of trucks of type (Y_j) needed to move ($X_i\beta_{ijk}$) tons of commodity (X_i) by all body types can be expressed as:

$$Y_j = \sum_{k=1}^{k=19} \frac{X_i\beta_{ijk}}{\omega_{ijk}} = X_i \sum_{k=1}^{k=9} \frac{\beta_{ijk}}{\omega_{ijk}} \tag{9}$$

Finally, the total number of trucks assigned to move commodity (X_i) and the total number of trucks assigned to move all commodities are given as:

$$\sum_{j=1}^{j=5} Y_j = X_i \sum_{j=1}^{j=5} \sum_{k=1}^{k=9} \frac{\beta_{ijk}}{\omega_{ijk}} \tag{10}$$

$$Total_{Trucks} = \sum_{i=1}^{i=50} X_i \sum_{j=1}^{j=5} \sum_{k=1}^{k=9} \frac{\beta_{ijk}}{\omega_{ijk}} \tag{11}$$

The truck equivalency factor is therefore presented as:

$$TEF_{ijk} = \frac{\beta_{ijk}}{\omega_{ijk}} \tag{12}$$

Where
i is the commodity index (1, 2, … 43)
j is the truck configuration group index (1, 2, … 5)
k is the tuck body-type index (1, 2, … 9)
$X_i$is the tonnage of commodity (i)
Y_j is the number of trucks in truck configuration group (j)
β_{ijk} represents the fraction of commodity (i) moved by truck type (j) with body type (k)
ω_{ijk} denotes the mean payload of truck type j with body type k transporting commodity i
$X_i\beta_{ijk}$is the tonnage of commodity (X_i) carried by truck type (j) and body type (k)
$X_i\beta_{ijk}/\omega_{ijk}$ represents the number of trucks of type (j) and body type (k) required to move ($X_i\beta_{ijk}$) tonnes

The truck equivalency factors were applied to the commodity flows allocated for each truck configuration to create a disaggregated data set describing the total number of loaded trucks required to move the freight between the zones. The empty truck percentage for a given truck and body type configuration was added to estimate the total long distance truck population. Employing the above procedure, Tables 8 & 9 represents the equivalent TEU imported and exported from the port of Mombasa disintegrated into the loaded and empty trucks.

Table 8: Annual Imports Truck Equivalent Units

Year	2010	2011	2012	2013	2014	2015	2020	2025	2030
Model Forecasts (‘000 tonnes)	16632	16874	18756	19921	21567	22971	32582	42765	48736
TEU	303787	308207	342582	363861	393926	419570	595117	781112	890173
Loaded Trucks	297484	301813	335475	356312	385753	410865	582770	764906	871704
Empty Trucks	6303	6394	7108	7549	8173	8705	12347	16206	18469

Table 9: Annual Exports Truck Equivalent Units

Year	2010	2011	2012	2013	2014	2015	2020	2025	2030
Model Forecasts (‘000 tonnes)	1854	2173	2048	2242	2654	3367	5722	6692	7621
TEU	287146	300762	321872	337651	368921	389673	543251	725983	875254
Loaded Trucks	91293	95622	102334	107351	117292	123890	172718	230814	278273
Empty Trucks	195853	205140	219538	230300	251629	265783	370533	495169	596981

The results were compared with the actual figures obtained from KPA in order to determine the validity of the model results. With an R^2 of 0.9606, the model results are reasonable and compares well with the actual values of TEU’s.

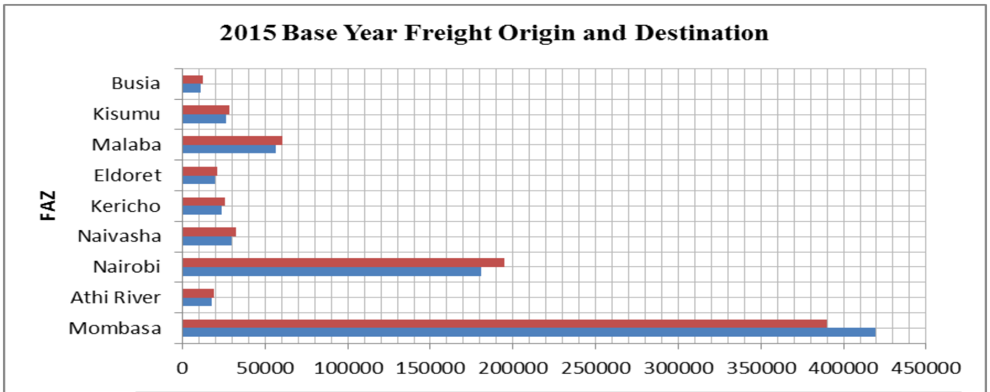
3.3 Trip Distribution

Freight movements were defined as O-D pairs originating from and attracted to each FAZ. The trip distribution model chosen for the study was the doubly constraint Furness growth factor model as the freight traffic origins origination and attractions from the external to external FAZ including their growth rates are known for the base year. The Furness model balancing factors a_i and b_j is presented as Ortúzar and Willumsen (2011):

$$T_{ij} = t_{ij} * a_i * b_j * c_{ij} \tag{13}$$

Where
T_{ij} is the expanded total number of trips

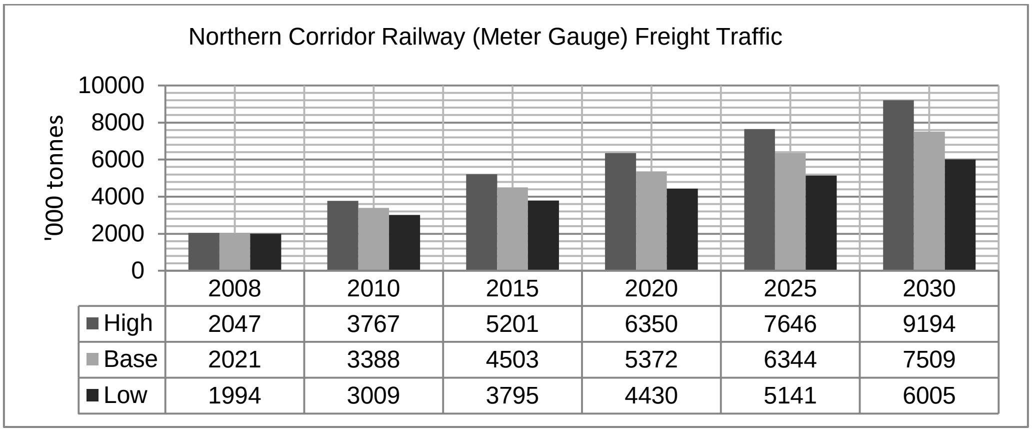
t_{ij} is the initial number of trips
$a_i \& b_j$ are the balancing factors
c_{ij} is the generalized cost of travel which accounts for travel time and cost of travel from FAZ i&j. The resulting calculated O-D for the 2015 base year is provided in Figure 3.



	Mombasa	Athi River	Nairobi	Naivasha	Kericho	Eldoret	Malaba	Kisumu	Busia
Attraction	389673	19155	194627	32149	25701	21051	60553	28511	12051
Generation	419570	17790	180758	29858	23870	19551	56238	26480	11192

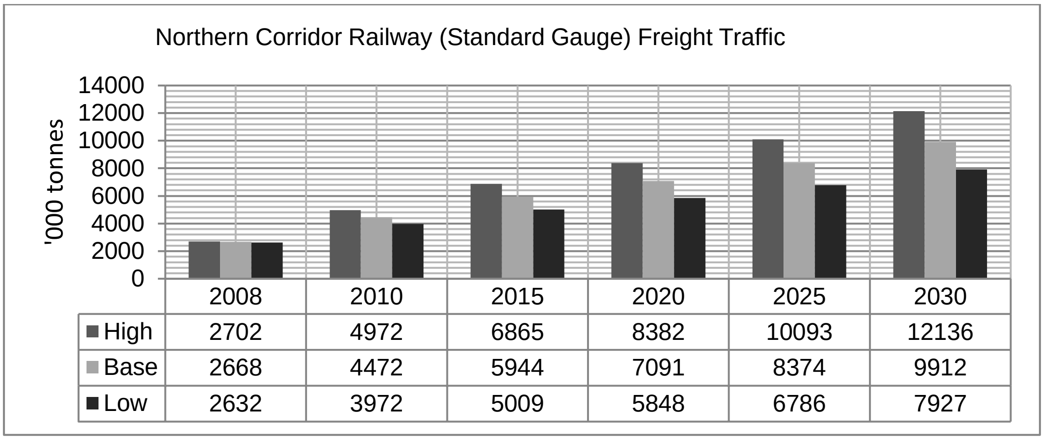
Figure 3: 2015 Base Year Freight Origins and Destinations
Note: The trip generation values for Mombasa are the total imports while attraction values are the total exports

In order to derive the associated Standard Gauge Railway Line freight demand, the demand assumptions based on the forecasts by the East Africa Community (EAC, 2009) Railway Masterplan study by CPCS as presented in Figures 4 & 5 were employed. It is noted from these forecasts that the existing Meter Gauge Railway Line (MGRL) only represents 7% of the total port of Mombasa traffic, however, it is predicted that the SGRL would result in an increase in rail freight demand by an average of about 20% from the existing values. These values were factored into the 2015 demand model and resulted into an O-D matrix provided in Figure 6 which was used as input into the VISUM model.



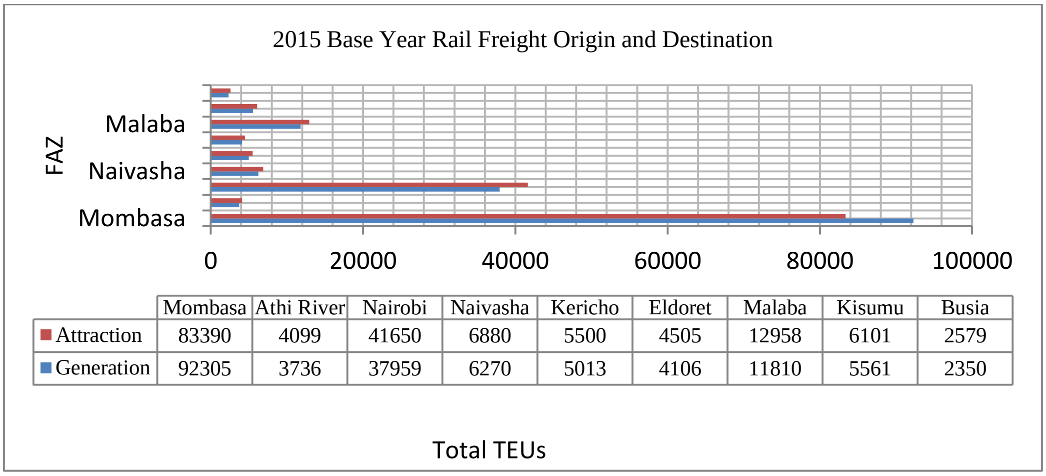
	2008	2010	2015	2020	2025	2030
High	2047	3767	5201	6350	7646	9194
Base	2021	3388	4503	5372	6344	7509
Low	1994	3009	3795	4430	5141	6005

Figure 4: Existing Meter Gauge Railway Line Freight Forecasts



	2008	2010	2015	2020	2025	2030
High	2702	4972	6865	8382	10093	12136
Base	2668	4472	5944	7091	8374	9912
Low	2632	3972	5009	5848	6786	7927

Figure 5: Standard Gauge Railway Line Freight Forecasts



	Mombasa	Athi River	Nairobi	Naivasha	Kericho	Eldoret	Malaba	Kisumu	Busia
Attraction	83390	4099	41650	6880	5500	4505	12958	6101	2579
Generation	92305	3736	37959	6270	5013	4106	11810	5561	2350

Figure 6: Standard Gauge Railway O-D Matrix

3.4 Trip Assignment

It was assumed that the network supply remained the same with no additional infrastructure investment or policy directions considered. Because there is no alternative route, traffic on links is assigned without consideration of whether or not there is adequate capacity or heavy congestion, the all-or-nothing (AON) traffic assignment procedure Ortúzar and Willumsen (2011) was adopted. In this method the trips from any origin zone to any destination zone are loaded onto a single path between them. This assignment is constrained by the highway network's current capacity and assumes that the travelers may not have perfect information concerning network congestion and delay and/or perceive travel costs.

The GEH statistic (equation 14) criterion was applied to assess the difference between modeled values and observed values. The GEH of two traffic volumes, usually measured and predicted or simulated is defined as UK Highways Agency (1992). A GEH index of less than 5.0 in a measurement point is considered a good match between the modelled and observed volumes, and 85% of the volumes in a traffic model should have a GEH less than 5.0 for all measurement points. The results of GEH estimates are provided in Table 10.

$$GEH = \sqrt{\frac{(AssignedVolume - Count)^2}{(\frac{AssignedVolume + Count}{2})}} \tag{14}$$

Table 10: Traffic Assignment Calibration Results

Station	2010 GEH	2015 GEH
Bachuma Gate	2.58	4.24
Machakos Turn-off	1.50	4.54
Athi River	4.16	4.95
Maimaiu	3.61	7.50
Mau Summit	4.38	8.99
Kericho	3.32	4.59
Otonglo	8.73	3.05
Eldoret Total	2.72	2.73

The trip assignment stage calibration successfully resulted in a high consistency of the model volumes when compared with the observed data at the various count location along the corridor and within generally accepted recommended GEH statistic ranges discussed in the preceding section. The calibrated network therefore provided a robust framework for accurately predicting future link volumes and assessment of future strategic transport conditions.

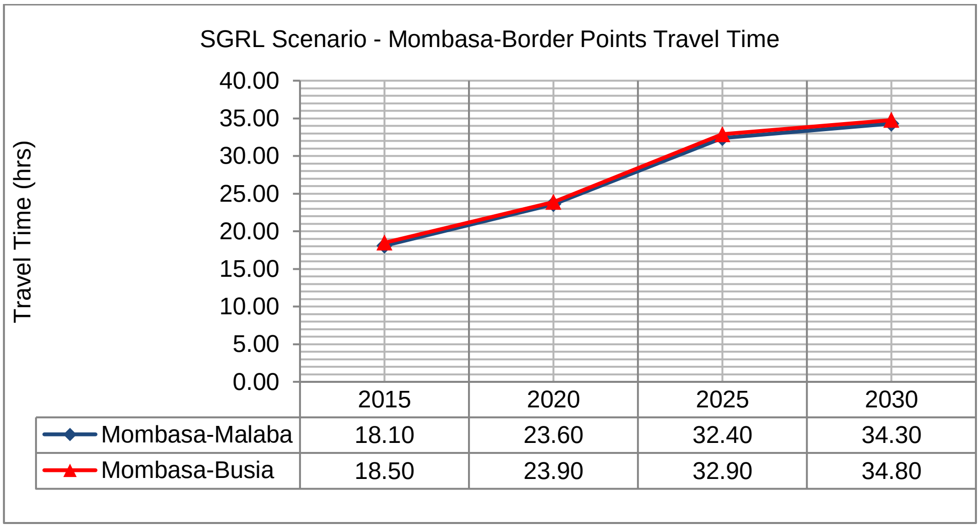
4.0 Results and Discusion

4.1 Introduction

The roadway capacity analysis was intended to provide information on a set of performance measures for each highway link. The analysis assumes the status quo network characteristics with no additional infrastructure investment or policy directions considered. Roadway capacity-related performance measures include traffic volume, travel time, link delay, congested speed, and service to flow ratio. These performance measures were estimated for the 2015 base year as well as the forecast year 2030. Differences in these performance measures between the base year and the forecast year are indications of changes in congestion and the ability of the highway system capacity to support freight transportation system demand in the future. The results of the network performance analysis are discussed as follows:

4.2 Network Travel Time

The SGRL intervention results in a considerable reduction in travel time along the two spurs of the Northern Corridor. The Mombasa-Busia spur records 14.2% reduction and15.4% reduction for Mombasa-Malaba spurs were the SGRL to be in operation in 2015. As shown in Figure 7, similar trends in reduction in travel time would be observed in the forecast years 2020, 2025 and 2030 however with reductions not as significant as in the 2015 base case. The decreasing trend in reduction in travel time is attributed to the fact that the railway line would be reaching its capacity and the demand on the road network will begin to rise after 2020.Travel time reductions are also more pronounced with the SGRL intervention where 12.8% and13.6% reductions in travel time are realized along Mombasa-Busia and Mombasa-Malaba spurs respectively during the 2015 base year. The travel time reductions are also more significant for the 2020, 2025 and 2030 scenarios. Significant reductions in travel times are realized between Mombasa-Mariakani, Machakos Turn-off, Museum Hill roundabout and Mai Mahiu sections. Overall, over the analysis years, SGRL results in much travel time savings.

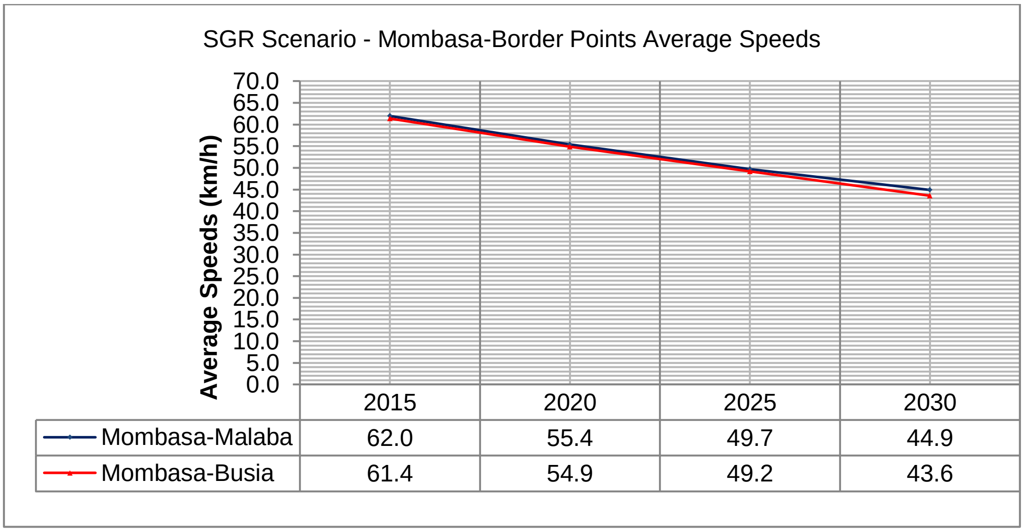


	2015	2020	2025	2030
Mombasa-Malaba	18.10	23.60	32.40	34.30
Mombasa-Busia	18.50	23.90	32.90	34.80

Figure 7: Network Travel Time

4.3 Network Average Speeds

The model network assignment results shown in Figure 8 reveal that there will be network speed gains along the two spurs of the Northern Corridor for the 2015 base year. However, these benefits will be short lived and will begin to increase at a decreasing rate from the 2020, 2025 and 2030 forecast years though still achieving a slightly high average network speed. The Mombasa – Mariakani, and link sections do witness significant speed reductions over the 2020, 2025 and 2030 forecast years.



	2015	2020	2025	2030
Mombasa-Malaba	62.0	55.4	49.7	44.9
Mombasa-Busia	61.4	54.9	49.2	43.6

Figure 8: Network Average Speed

4.4 Network Capacities

As presented in Figure 9, the SGRL will result in significant improvements in capacity along the network for the base year 2015 and the forecast year 2020. However, there are corridor sections that will witness capacity constraints including Changamwe – Mariakani, Machakos Turnoff - Athi River, Athi River - Museum Hill Roundabout, Museum Hill Roundabout - Mai Mahiu during the 2025 and 2030 forecast years. Overall, the SGRL will have significant capacity impacts along the corridor.

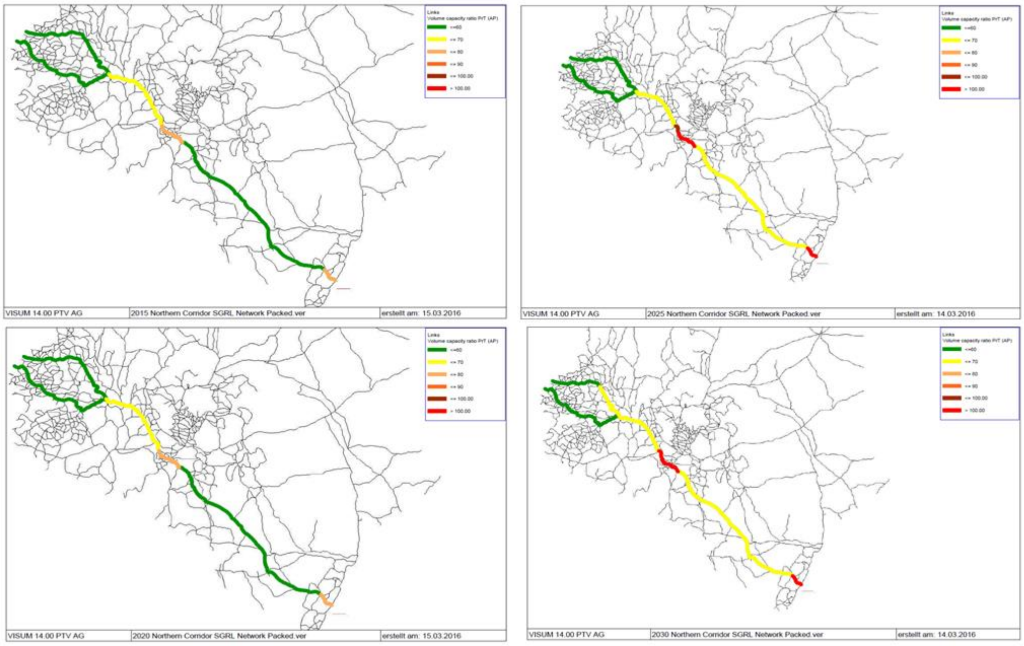


Figure 9: Network Capacities

4.5 Network Emissions

Figure 10 shows that the SGRL will result in substantial reduction of Ozone and Sulphur dioxide concentration along the network up to the forecast year 2020. The Machakos Turn-off – Athi River, Athi River – Museum Hill Roundabout and Museum Hill Roundabout sections will surpass the acceptable concentration levels during the forecast year 2020. In 2030, the network will perform fairly well except the Changamwe – Mariakani and Machakos Turn-off – Museum Hill Roundabout sections that will exceed the acceptable WHO standards for Ozone of 100µg/m^3 (WHO, 2006).

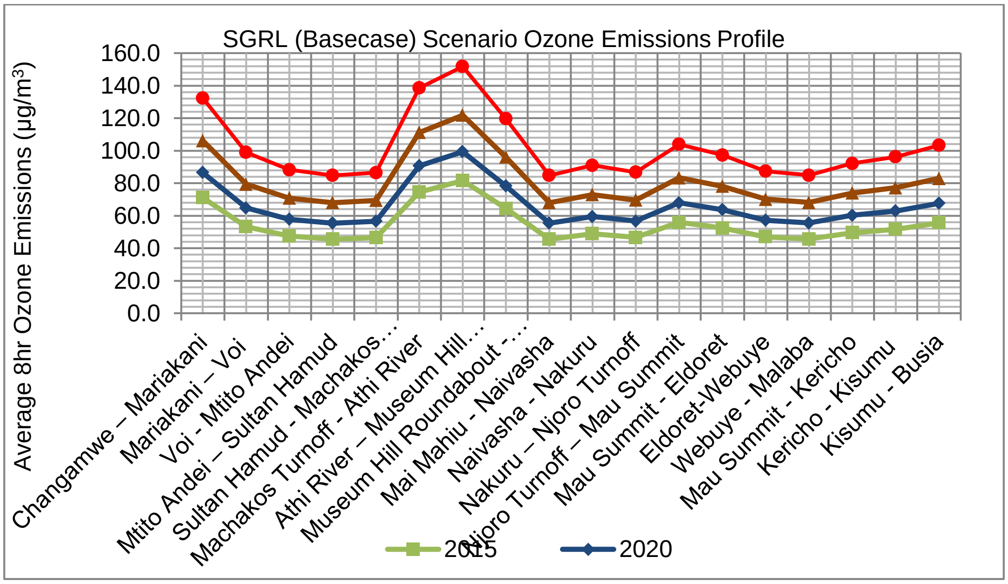


Figure 10: Ozone Emissions Profile

5.0 Conclusions

The key headline network performance conclusions are as follows:

1. Under the plausible economic growth regime, the freight demand along the Northern Corridor network is expected to grow at an average rate of 5.5% between 2015 and 2030. The SGRL will only divert a maximum of 20% of freight demand from the road network.

2. The realization of the Standard Gauge Railway Line (SGRL) project is expected to reduce capacity on the network, reduce travel time, minimize emissions concentrations and improve the entire network reliability. However, this will depend on the rail modal split capacity, and as such the excess capacity will only be handled by the road network which in turn will cause capacity constraints beyond the 2025.

3. Beyond 2025, the concentration of Ozone emissions along the corridor is expected to exceed the acceptable World Health Organization (WHO) thresholds of 100µg/m^3 and with higher concentrations within Mombasa – Mariakani section, Athi River to Mai Mahiu sections of the corridor.

4. These performance indicators can be used as trigger points in determining where and when infrastructure improvement options or policy options can be

considered. In the next series, different interventions required to address the network constraints highlighted herein have been modelled and their impacts quantified.

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