# FORMULATION OF CONCAVE-CONVEX FRACTIONAL PROGRAMMING MODEL FOR BANK PORTFOLIO SELECTIONS 

M. I. OKONNA AND E. O. EFFANGA


#### Abstract

In this paper, a concave-convex fractional programming model for bank portfolio selections is formulated. We have transformed the model into a concave quadratic programming problem and developed a technique for its solution. A real life application of the model is performed with twelve banks in Nigeria. The optimal solution determined by the proportion of investment to be made by an investor in each bank in order to maximize the expected returns at minimum risk is highlighted. However, the computational results show that the proposed model can generate a favourable portfolio strategy according to the investor's satisfactory degree. The trade-off curve also indicates the amount of risk that is commensurate with a particular expected return.


Key words: concave-convex, fractional programming problem, optimization, transformation

### 1.1 INTRODUCTION

The effectiveness/workability of a system is most times characterised by a ratio of technical and economic problems. Maximizing system efficiency gives rise to fractional programs. The frequently occurring objectives are maximization of productivity, maximization of return on investment, maximization of return/risk, minimization of cost/time and maximization of output/input. Other non-economic applications arise from information theory, applied mathematics and physics among others (Schaible (2000)). Most of these applications are on linear fractional programming where both the numerator and denominator of the objective function are linear. In real life situations linear fractional models arise in decision making such as construction planning, economic and commercial planning, production planning, financial and corporate planning, health care and hospital planning, bank balance sheet management, water resources management. Thus, mathematical models taking objective function as a ratio of two linear functions have many applications in financial planning. Indeed, in such situations, it is often a question of optimizing a ratio: debt/equity, output/employee, actual cost/standard cost, profit/cost, inventory/sales, risk asset/capital, student/cost, doctor/patient and so on subject to some constraints. If the constraints are linear, we obtain the linear fractional programming problem (LFPP) Pandian et al. (2013), Mehrjerdi (2010). Therefore, Linear Fractional programming problem deals with that class of mathematical programming problem in which the relation between the variables in the problem are linear, the constraint relation are in linear form and the objective function to be optimized is a ratio of two linear functions. Narayanamoorthy and Kalyani (2015). In the literature several methods have been recommended for the solution of LFPP. LFPP has drawn the interest of many researchers since it is widely applied in many important fields. In recent
times, much has been done with respect to propounding optimal solution to fractional programming problems. Optimization of fractional programming problem involves several methods of transforming the problem to a linear or quadratic form in diverse areas of the application. This has been done using various techniques and by different researchers which include: Harvey (1968), Bitran and Novaes (1972), Charnes and Cooper (1973), Schaible (1981), Hasan and Acharjee (2011), Narayanamoorthy and Kalyani (2015), Schaible (1980), Singh (1981), Verna et al. (1990), Tantawy (2008), Xiao (2010), Penclaim and Jayalakshmi (2013), Lokhande et al (2013).

### 1.2 Non- linear fractional programming

In linear programming the aim is to maximize or minimize a linear function subject to linear constraints. In many interesting maximization and minimization problems the objective function may not be a linear function and some of the constraints may not be linear constraints. Such an optimization problem is called a Non-linear programming problem (NLP) Winston(1994). Literature on nonlinear fractional programming include the following: Sulaiman (2013), Abdulrahim (2014), Frag et al (2009), Shen et al. (2009),

Bisoi et al (2011), Sharma et.al. (2011), Abdulrahim (2014). In this work, we intend to look at the Non-linear fractional programming problem where the objective function is a rational function in which the numerator is linear and the denominator is quadratic with linear constraint. Portfolio selection application of maximization of return on risk which is expected to yield a global optimal solution is used.

### 2.0 GENERAL FRACTIONAL PROGRAMMING MODEL

The general fractional programming problem is of the form:
$\operatorname{Max} Z=\frac{f(x)}{g(x)}, x \in s$
where

$$
\begin{aligned}
& S=\left\{x \in R^{n}: h x \leq b ; b \subset R^{n}\right\}, \\
& g(x) \geq 0
\end{aligned}
$$

### 3.0 Formulation of the Model for Bank Portfolio Selections

### 3.1 Definition of variables and parameters

Let
$x_{i}=$ Proportion of investment made in each bank; $\mathrm{i}=1,2, \ldots, 12$
$L_{i}=$ Liquidity of the ith bank
$E_{i}=$ Earnings per shares of the ith bank
$R_{i}=$ Return on investment in the $i t h$ bank
$L=$ The lowest acceptable expected Liquidity per unit money invested in the entire portfolio.
$E=$ The lowest acceptable earnings per share per unit money invested in the entire portfolio
$\mu_{i}=$ Expected return on investment in the $\mathrm{i}^{\text {th }}$ bank
$\sigma_{i j}=$ Covariance of the expected returns on security i and j
$R_{p}=$ Return for the portfolio

### 3.2 Formulation of the objective function

The return for the portfolio $\left(R_{p}\right)$ is given by
$R_{t}=\sum_{i=1}^{12} R_{i} x_{i}$

Taking expectations of both sides of equation (2) we obtain
$E\left[R_{i}\right]=\sum_{i=1}^{12} E\left[R_{i}\right] x_{i}$

This may be rewritten as
$\mu_{R t}=\sum_{i=1}^{12} \mu_{i} x_{i}$
$f(x)=\sum_{i=1}^{12} \mu_{i} x_{i}$

Where
$f(x)=\mathrm{E}[R]$ and $\mu_{i}=\mathrm{E}\left[R_{i}\right]$
The risk of the portfolio as measured by variance of the total returns is given by
$\operatorname{Var}(R)=\sum_{i=1}^{12} x_{i}^{2} \operatorname{Var}\left(R_{i}\right)+\sum_{i=1}^{12} \sum_{j=1}^{12} x_{i} x_{j} \operatorname{Cov}\left(R_{i}, R_{j}\right)$
This may be written in an expanded form as

$$
\begin{aligned}
& g(x)=x_{1}^{2} \sigma_{1}^{2}+x_{2}^{2} \sigma_{2}^{2}+x_{3}^{2} \sigma_{3}^{2}+x_{4}^{2} \sigma_{4}^{2}+x_{5}^{2} \sigma_{5}^{2}+x_{6}^{2} \sigma_{6}^{2}+x_{7}^{2} \sigma_{7}^{2}+x_{8}^{2} \sigma_{8}^{2}+x_{9}^{2} \sigma_{9}^{2}+x_{10}^{2} \sigma_{10}^{2}+x_{11}^{2} \sigma_{11}^{2}+x_{12}^{2} \sigma_{12}^{2} \\
& +2 x_{1} x_{2} \sigma_{12}+2 x_{1} x_{3} \sigma_{13}+2 x_{1} x_{4} \sigma_{14}+2 x_{1} x_{5} \sigma_{15+} 2 x_{1} x_{6} \sigma_{16}+2 x_{1} x_{7} \sigma_{17}+2 x_{1} x_{8} \sigma_{18}+2 x_{1} x_{9} \sigma_{19}+2 x_{1} x_{10} \sigma_{1,10} \\
& +2 x_{1} x_{11} \sigma_{1,11}+2 x_{1} x_{12} \sigma_{1,12}+2 x_{2} x_{3} \sigma_{23}+2 x_{2} x_{4} \sigma_{24}+2 x_{2} x_{5} \sigma_{25}+2 x_{2} x_{6} \sigma_{26}+2 x_{2} x_{7} \sigma_{27}+2 x_{2} x_{8} \sigma_{28} \\
& +2 x_{2} x_{9} \sigma_{29}+2 x_{2} x_{10} \sigma_{2,10}+2 x_{2} x_{11} \sigma_{2,11}+2 x_{2} x_{12} \sigma_{2,12}+2 x_{3} x_{4} \sigma_{34}+2 x_{3} x_{5} \sigma_{35}+2 x_{3} x_{6} \sigma_{36}+2 x_{3} x_{7} \sigma_{37} \\
& +2 x_{3} x_{8} \sigma_{38}+2 x_{3} x_{9} \sigma_{39}+2 x_{3} x_{10} \sigma_{3,10}+2 x_{3} x_{11} \sigma_{3,11}+2 x_{3} x_{12} \sigma_{3,12}+2 x_{4} x_{5} \sigma_{45}+2 x_{4} x_{6} \sigma_{46}+2 x_{4} x_{7} \sigma_{47} \\
& +2 x_{4} x_{8} \sigma_{48}+2 x_{4} x_{9} \sigma_{49}+2 x_{4} x_{10} \sigma_{4,10}+2 x_{4} x_{11} \sigma_{4,11}+2 x_{4} x_{12} \sigma_{4,12}+2 x_{5} x_{6} \sigma_{56}+2 x_{5} x_{7} \sigma_{57}+2 x_{5} x_{8} \sigma_{58} \\
& +2 x_{5} x_{9} \sigma_{59}+2 x_{5} x_{10} \sigma_{5,10}+2 x_{5} x_{11} \sigma_{5,11}+2 x_{5} x_{12} \sigma_{5,12}+2 x_{6} x_{7} \sigma_{67}+2 x_{6} x_{8} \sigma_{68}+2 x_{6} x_{9} \sigma_{69}+2 x_{6} x_{10} \sigma_{6,10} \\
& +2 x_{6} x_{11} \sigma_{6,11}+2 x_{6} x_{12} \sigma_{6,12}+2 x_{7} x_{8} \sigma_{78}+2 x_{7} x_{9} \sigma_{79}+2 x_{7} x_{10} \sigma_{7,10}+2 x_{7} x_{11} \sigma_{7,11}+2 x_{7} x_{12} \sigma_{7,12}+2 x_{8} x_{9} \sigma_{89} \\
& +2 x_{8} x_{10} \sigma_{8,10}+2 x_{8} x_{11} \sigma_{8,11}+2 x_{8} x_{12} \sigma_{8,12}+2 x_{9} x_{10} \sigma_{9,10}+2 x_{9} x_{11} \sigma_{9,11}+2 x_{9} x_{12} \sigma_{9,12}+2 x_{10} x_{11} \sigma_{10,11} \\
& +2 x_{10} x_{12} \sigma_{10,12}+2 x_{11} x_{12} \sigma_{11,12}
\end{aligned}
$$

Therefore, the objective function of the portfolio selection model is formulated thus:

$$
\begin{equation*}
\mathrm{Z}=\frac{f(x)}{g(x)} \tag{5}
\end{equation*}
$$

This objective function is to be maximized.

### 3.3 Formulation of the constraint

The constraints are liquidity, earnings per shares and total assets and are formulated thus:
The liquidity constraint is
$\sum_{i=1}^{12} L_{i} x_{i} \leq L$

The earnings per share constraint is
$\sum_{i=1}^{12} E_{i} x_{i} \leq E$
The total asset constraint is given by
$\sum_{i=1}^{12} x_{i}=1$

Non-negativity constraints are
$x_{i} \geq 0, \quad i=1,2, \ldots, 12$
The proportion must be nonnegative

### 3.4 The complete model

$\operatorname{Max} \mathrm{Z}=\frac{f(x)}{g(x)}$
Subject to:
$\sum_{i=1}^{12} L_{i} x_{i} \leq L$
$\sum_{i=1}^{12} E_{i} x_{i} \leq E$
$\sum_{i=1}^{12} x_{i}=1$
$x_{i} \geq 0, \quad i=1,2, \ldots, 12$

### 3.5 The model excluding the liquidity and earnings per share constraints

$\operatorname{Max} \mathrm{Z}=\frac{f(x)}{g(x)}$
Subject to:
$\sum_{i=1}^{12} x_{i}=1$
$x_{i} \geq 0$,

### 3.6 The conventional portfolio selection model

$\operatorname{Min} Z=g(x)$
Subject to:
$\sum_{i=1}^{12} \mu_{i} x_{i}=\mu$
$\sum_{i=1}^{12} x_{i}=1$
$x_{i} \geq 0$

### 4.0 Model Solution

## Lemma 1:

$$
\operatorname{Max}\left\{\frac{f(x)}{g(x)}\right\} \cong-\operatorname{Max}\left\{\frac{-g(x)}{f(x)}\right\}
$$

## Proof:

$$
\operatorname{Max}\left\{\frac{1}{p(x)}\right\} \cong \operatorname{Min}\{p(x)\} \cong-\operatorname{Max}\{-p(x)\}
$$

Now letting $p(x)=\frac{g(x)}{f(x)}$
we obtain

$$
\operatorname{Max}\left\{\frac{f(x)}{g(x)}\right\} \cong-\operatorname{Max}\left\{\frac{-g(x)}{f(x)}\right\}
$$

Lemma 2: If $g(x)$ is convex, then $\sqrt{g(x)}$ is also convex and vice versa.
Lemma 3: If $g(x)$ is convex, then $-g(x)$ is concave.
Theorem 1: If $f(x)$ is concave and $g(x)$ is convex, then the concave-convex fractional programming model can be transformed to a concave programming model.

Proof:

By lemma (1), the concave-convex programming model (10-13) is equivalent to

$$
\begin{equation*}
\operatorname{Max} Z=\frac{-g(x)}{f(x)} \tag{16}
\end{equation*}
$$

Subject to:
$\sum_{i=1}^{12} L_{i} x_{i} \leq L$
$\sum_{i=1}^{12} x_{i}=1$
$x_{i} \geq 0, \quad i=1,2, \ldots, 12$

By lemma 2, equation (10) is equivalent to
$-\operatorname{Max}\left\{Z=\frac{-\sqrt{g(x)}}{f(x)}\right\}$
Subject to:

$$
\sum_{i=1}^{12} L_{i} x_{i} \leq L
$$

$\sum_{i=1}^{12} E_{i} x_{i} \leq E$
$\sum_{i=1}^{12} x_{i}=1$
$x_{i} \geq 0, \quad i=1,2, \ldots, 12$

Let $f(x)=\sum_{j=1}^{12} \mu_{j} x_{j}=t$
$g(x)=\sum_{i=1}^{12} \sum_{j=1}^{12} q_{i j} x_{i} x_{j}$
$x_{j}=t y_{j} \Rightarrow \frac{x_{j}}{t}=y_{j}$ and $r=\frac{1}{t} \Rightarrow r t=1$
Then the model becomes
$-\operatorname{Max}\left\{Z^{\prime}=-\left[\sum_{i=1}^{m} \sum_{j=1}^{n} q_{i j} y_{i} y_{j}\right]^{\frac{1}{2}}\right\}$
Subject to:
$\sum_{j=1}^{12} L_{j} y_{j}-L r \leq 0$
$\sum_{j=1}^{12} E_{j} y_{j}-E r \leq 0$
$\sum_{i=1}^{12} y_{i}-r \leq 0$
$\sum_{j=1}^{12} \mu_{j} y_{j}=1$
$y_{j} \geq 0, j=1,2, \ldots, 12$

Finally, by Lemma (3), the model becomes:
$-\operatorname{Max}\left\{Z^{\prime}=-\sum_{i=1}^{m} \sum_{j=1}^{n} q_{i j} y_{i} y_{j}\right\}$
Subject to:
$\sum_{j=1}^{12} L_{j} y_{j}-L r \leq 0$
$\sum_{j=1}^{12} E_{j} y_{j}-E r \leq 0$
$\sum_{i=1}^{12} y_{i}-r \leq 0$

$$
\begin{align*}
& \sum_{j=1}^{12} \mu_{j} y_{j}=1  \tag{28}\\
& y_{j} \geq 0, j=1,2, \ldots, 12 \tag{29}
\end{align*}
$$

Equation (24) - (29) is a concave quadratic programming model.

### 4.3 The transformed model excluding the liquidity and earnings per share constraints

$-\operatorname{Max}\left\{Z^{\prime}=-\sum_{i=1}^{m} \sum_{j=1}^{n} q_{i j} y_{i} y_{j}\right\}$
Subject to:

$$
\begin{aligned}
& \sum_{i=1}^{12} y_{i}-r \leq 0 \\
& \sum_{j=1}^{12} \mu_{j} y_{j}=1 \\
& y_{j} \geq 0, j=1,2, \ldots, 12
\end{aligned}
$$

### 4.4 Solving the Model with real data

### 4.4.1 Data

Based on the data collected from the Nigerian Stock Exchange on the annual financial statement of twelve banks, the mean, variance, covariance, Hessian matrix are determined. Optimal solution of the concave-convex fractional programming model, the transformed model and the conventional portfolio selection model is obtained. Tables and graph are used for the respective interpretations and are subsequently discussed.

The transformed portfolio selection model to concave quadratic programming problem is given by

$$
\begin{aligned}
& \operatorname{MaxZ} Z^{\prime}=-\left(0.00863 y_{1}^{2}+0.06414 y_{2}^{2}+0.09550 y_{3}^{2}+0.00476 y_{4}^{2}+0.00284 y_{5}^{2}+0.27322 y_{6}^{2}\right. \\
& +0.05560 y_{7}^{2}+0.01578 y_{8}^{2}+0.00352 y_{9}^{2}+1.2962 y_{10}^{2}+0.01892 y_{11}^{2}+0.01578 y_{12}^{2}+0.00769 y_{1} y_{2} \\
& -0.00220 y_{1} y_{3}-0.00030 y_{1} y_{4}+0.00402 y_{1} y_{5}-0.01012 y_{1} y_{6}-0.01896 y_{1} y_{7}-0.00331 y_{1} y_{8} \\
& -0.00374 y_{1} y_{9}-0.03624 y_{1} y_{10}-0.00885 y_{1} y_{11}-0.00329 y_{1} y_{12}+0.00614 y_{2} y_{3}+0.00502 y_{2} y_{4} \\
& +0.003734 y_{2} y_{5}+0.04720 y_{2} y_{6}-0.00010 y_{2} y_{7}+0.01676 y_{2} y_{8}+0.00496 y_{2} y_{9}+0.10220 y_{2} y_{10} \\
& -0.00403 y_{2} y_{11}+0.01441 y_{2} y_{12}+0.00212 y_{3} y_{4}+0.04023 y_{3} y_{5}+0.04998 y_{3} y_{6}+0.01699 y_{3} y_{7} \\
& +0.02148 y_{3} y_{8}+0.00604 y_{3} y_{9}+0.21728 y_{3} y_{10}+0.00721 y_{3} y_{11}+0.01654 y_{3} y_{12}+0.00620 y_{4} y_{5} \\
& -0.00846 y_{4} y_{6}+0.00746 y_{4} y_{7}+0.00722 y_{4} y_{8}+0.00142 y_{4} y_{9}-0.02439 y_{4} y_{10}+0.00638 y_{4} y_{11} \\
& +0.00762 y_{4} y_{12}-0.00660 y_{5} y_{6}+0.00236 y_{5} y_{7}+0.01634 y_{5} y_{8}+0.00229 y_{5} y_{9}+0.07170 y_{5} y_{10} \\
& +0.00349 y_{5} y_{11}+0.01510 y_{5} y_{12}+0.04084 y_{6} y_{7}-0.00760 y_{6} y_{8}+0.01631 y_{6} y_{9}+0.02780 y_{6} y_{10} \\
& -0.00540 y_{6} y_{11}-0.01180 y_{6} y_{12}+0.01808 y_{7} y_{8}+0.01174 y_{7} y_{9}+0.00374 y_{7} y_{10}+0.00281 y_{7} y_{11} \\
& +0.01796 y_{7} y_{12}+0.00428 y_{8} y_{9}+0.03417 y_{8} y_{10}+0.01232 y_{8} y_{11}+0.01564 y_{8} y_{12}+0.02455 y_{9} y_{10} \\
& \left.+0.00419 y_{9} y_{11}+0.00430 y_{9} y_{12}-0.01035 y_{10} y_{11}+0.02481 y_{10} y_{12}+0.01238 y_{11} y_{12}\right)
\end{aligned}
$$

Subject to:

$$
\begin{aligned}
& 0.1519 y_{1}+0.2378 y_{2}+0.1868 y_{3}+0.3723 y_{4}+0.0809 y_{5}+0.1759 y_{6}+0.1859 y_{7}+0.2131 y_{8} \\
& +0.0388 y_{9}+0.4346 y_{10}+0.1147 y_{11}+0.3813 y_{12}-30.888 r \leq 0 \\
& 1.2517 y_{1}+0.7267 y_{2}+0.2017 y_{3}+0.3100 y_{4}+0.7067 y_{5}+0.0700 y_{6}+0.2550 y_{7}+2.2233 y_{8} \\
& +0.7350 y_{9}+0.9983 y_{10}+0.8900 y_{11}+1.9617 y_{12}-123.96 r \leq 0 \\
& y_{1}+y_{2}+y_{3}+y_{4}+y_{5}+y_{6}+y_{7}+y_{8}+y_{9}+y_{10}+y_{11}+y_{12}-r \leq 0 \\
& 0.0209 y_{1}+0.0080 y_{2}+0.0170 y_{3}+0.0097 y_{4}+0.010 y_{5}+0.0036 y_{6}+0.0046 y_{7}+0.0390 y_{8} \\
& +0.0092 y_{9}+0.0474 y_{10}+0.0068 y_{11}+0.0241 y_{12}-r=1 \\
& y_{j} \geq 0, j=1,2, \ldots, 12
\end{aligned}
$$

The transformed model excluding the liquidity and earnings per share constraint is given by
$M a x Z^{\prime}=-\left(0.00863 y_{1}^{2}+0.06414 y_{2}^{2}+0.09550 y_{3}^{2}+0.00476 y_{4}^{2}+0.00284 y_{5}^{2}+0.27322 y_{6}^{2}\right.$
$+0.05560 y_{7}^{2}+0.01578 y_{8}^{2}+0.00352 y_{9}^{2}+1.2962 y_{10}^{2}+0.01892 y_{11}^{2}+0.01578 y_{12}^{2}+0.00769 y_{1} y_{2}$
$-0.00220 y_{1} y_{3}-0.00030 y_{1} y_{4}+0.00402 y_{1} y_{5}-0.01012 y_{1} y_{6}-0.01896 y_{1} y_{7}-0.00331 y_{1} y_{8}$
$-0.00374 y_{1} y_{9}-0.03624 y_{1} y_{10}-0.00885 y_{1} y_{11}-0.00329 y_{1} y_{12}+0.00614 y_{2} y_{3}+0.00502 y_{2} y_{4}$
$+0.003734 y_{2} y_{5}+0.04720 y_{2} y_{6}-0.00010 y_{2} y_{7}+0.01676 y_{2} y_{8}+0.00496 y_{2} y_{9}+0.10220 y_{2} y_{10}$
$-0.00403 y_{2} y_{11}+0.01441 y_{2} y_{12}+0.00212 y_{3} y_{4}+0.04023 y_{3} y_{5}+0.04998 y_{3} y_{6}+0.01699 y_{3} y_{7}$
$+0.02148 y_{3} y_{8}+0.00604 y_{3} y_{9}+0.21728 y_{3} y_{10}+0.00721 y_{3} y_{11}+0.01654 y_{3} y_{12}+0.00620 y_{4} y_{5}$
$-0.00846 y_{4} y_{6}+0.00746 y_{4} y_{7}+0.00722 y_{4} y_{8}+0.00142 y_{4} y_{9}-0.02439 y_{4} y_{10}+0.00638 y_{4} y_{11}$
$+0.00762 y_{4} y_{12}-0.00660 y_{5} y_{6}+0.00236 y_{5} y_{7}+0.01634 y_{5} y_{8}+0.00229 y_{5} y_{9}+0.07170 y_{5} y_{10}$
$+0.00349 y_{5} y_{11}+0.01510 y_{5} y_{12}+0.04084 y_{6} y_{7}-0.00760 y_{6} y_{8}+0.01631 y_{6} y_{9}+0.02780 y_{6} y_{10}$
$-0.00540 y_{6} y_{11}-0.01180 y_{6} y_{12}+0.01808 y_{7} y_{8}+0.01174 y_{7} y_{9}+0.00374 y_{7} y_{10}+0.00281 y_{7} y_{11}$
$+0.01796 y_{7} y_{12}+0.00428 y_{8} y_{9}+0.03417 y_{8} y_{10}+0.01232 y_{8} y_{11}+0.01564 y_{8} y_{12}+0.02455 y_{9} y_{10}$
$\left.+0.00419 y_{9} y_{11}+0.00430 y_{9} y_{12}-0.01035 y_{10} y_{11}+0.02481 y_{10} y_{12}+0.01238 y_{11} y_{12}\right)$

## Subject to:

$y_{1}+y_{2}+y_{3}+y_{4}+y_{5}+y_{6}+y_{7}+y_{8}+y_{9}+y_{10}+y_{11}+y_{12}-r \leq 0$
$0.0209 y_{1}+0.0080 y_{2}+0.0170 y_{3}+0.0097 y_{4}+0.010 y_{5}+0.0036 y_{6}+0.0046 y_{7}+0.0390 y_{8}$ $+0.0092 y_{9}+0.0474 y_{10}+0.0068 y_{11}+0.0241 y_{12}-r=1$
$y_{j} \geq 0, j=1,2, \ldots, 12$
The conventional portfolio selection model is given as
$\operatorname{Min} Z=0.00863 x_{1}^{2}+0.06414 x_{2}^{2}+0.09550 x_{3}^{2}+0.00476 x_{4}^{2}+0.00284 x_{5}^{2}+0.27322 x_{6}^{2}+0.05560 x_{7}^{2}$ $+0.01578 x_{8}^{2}+0.00352 x_{9}^{2}+1.2962 x_{10}^{2}+0.01892 x_{11}^{2}+0.01578 x_{12}^{2}+0.00769 x_{1} x_{2}-0.00220 x_{1} x_{3}$ $-0.00030 x_{1} x_{4}+0.00402 x_{1} x_{5}-0.01012 x_{1} x_{6}-0.01896 x_{1} x_{7}-0.00331 x_{1} x_{8}-0.00374 x_{1} x_{9}$ $-0.03624 x_{1} x_{10}-0.00885 x_{1} x_{11}-0.00329 x_{1} x_{12}+0.00614 x_{2} x_{3}+0.00502 x_{2} x_{4}+0.003734 x_{2} x_{5}$ $+0.04720 x_{2} x_{6}-0.00010 x_{2} x_{7}+0.01676 x_{2} x_{8}+0.00496 x_{2} x_{9}+0.10220 x_{2} x_{10}-0.00403 x_{2} x_{11}$ $+0.01441 x_{2} x_{12}+0.00212 x_{3} x_{4}+0.04023 x_{3} x_{5}+0.04998 x_{3} x_{6}+0.01699 x_{3} x_{7}+0.02148 x_{3} x_{8}$ $+0.00604 x_{3} x_{9}+0.21728 x_{3} x_{10}+0.00721 x_{3} x_{11}+0.01654 x_{3} x_{12}+0.00620 x_{4} x_{5}-0.00846 x_{4} x_{6}$ $+0.00746 x_{4} x_{7}+0.00722 x_{4} x_{8}+0.00142 x_{4} x_{9}-0.02439 x_{4} x_{10}+0.00638 x_{4} x_{11}+0.00762 x_{4} x_{12}$ $-0.00660 x_{5} x_{6}+0.00236 x_{5} x_{7}+0.01634 x_{5} x_{8}+0.00229 x_{5} x_{9}+0.07170 x_{5} x_{10}+0.00349 x_{5} x_{11}$ $+0.01510 x_{5} x_{12}+0.04084 x_{6} x_{7}-0.00760 x_{6} x_{8}+0.01631 x_{6} x_{9}+0.02780 x_{6} x_{10}-0.00540 x_{6} x_{11}$ $-0.01180 x_{6} x_{12}+0.01808 x_{7} x_{8}+0.01174 x_{7} x_{9}+0.00374 x_{7} x_{10}+0.00281 x_{7} x_{11}+0.01796 x_{7} x_{12}$ $+0.00428 x_{8} x_{9}+0.03417 x_{8} x_{10}+0.01232 x_{8} x_{11}+0.01564 x_{8} x_{12}+0.02455 x_{9} x_{10}+0.00419 x_{9} x_{11}$ $+0.00430 x_{9} x_{12}-0.01035 x_{10} x_{11}+0.02481 x_{10} x_{12}+0.01238 x_{11} x_{12}$

Subject to:

$$
\begin{gathered}
0.0209 x_{1}+0.0080 x_{2}+0.0170 x_{3}+0.0097 x_{4}+0.010 x_{5}+0.0036 x_{6}+0.0046 x_{7} \\
+0.0390 x_{8}+0.0092 x_{9}+0.0474 x_{10}+0.0068 x_{11}+0.0241 x_{12} \\
x_{1}+x_{2}+x_{3}+x_{4}+x_{5}+x_{6}+x_{7}+x_{8}+x_{9}+x_{10}+x_{11}+x_{12}=1 \\
x_{i} \geq 0, i=1,2, \ldots, 12
\end{gathered}
$$

The result of the transformed model to quadratic program is as shown in table 1

## TABLE 1

## Optimal feasible solution to the transformed model

| Banks | $y_{1}$ | $Z^{\prime}$ | $r$ |
| :---: | :---: | :---: | :---: |
| 1 | 18.2234205 | 250.7913 | 45.7221903 |
| 2 | 0 |  |  |
| 3 | 0 |  |  |
| 4 | 0 |  |  |
| 5 | 0 |  |  |
| 6 | 0.18957332 |  |  |
| 7 | 0 |  |  |
| 8 | 11.1721626 |  |  |
| 9 | 13.6730391 |  |  |
| 10 | 0.14176062 |  |  |
| 11 | 0.33199689 |  |  |
| 12 | 1.9902372 |  |  |

TABLE 2

Optimal feasible solution to the original formulated portfolio selection model

| Banks | $x_{1}$ | $f(x)$ | $g(x)$ | $Z=\frac{f(x)}{g(x)}$ |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 0.398568 | 0.021871 | 0.001199 | 18.24103 |
| 2 | 0 |  |  |  |
| 3 | 0 |  |  |  |
| 4 | 0 |  |  |  |
| 5 | 0 |  |  |  |
| 6 | 0.004146 |  |  |  |
| 7 | 0 |  |  |  |
| 8 | 0.244349 |  |  |  |
| 9 | 0.299046 |  |  |  |
| 10 | 0.0031 |  |  |  |
| 11 | 0.007261 |  |  |  |
| 12 | 0.043529 |  |  |  |

TABLE 3

Optimal feasible solution to the transformed model excluding the liquidity and earnings per share constraint.

| Banks | $y_{1}$ | $Z^{\prime}$ | $r$ |
| :---: | :---: | :---: | :---: |
| 1 | 18.22622 | 250.7913 | 45.72383 |
| 2 | 0 |  |  |
| 3 | 0 |  |  |
| 4 | 0 |  |  |
| 5 | 0 |  |  |
| 6 | 0.18992 |  |  |
| 7 | 0 |  |  |
| 8 | 11.17278 |  |  |
| 9 | 13.66782 |  |  |
| 10 | 0.141884 |  |  |
| 11 | 0.338548 |  |  |
| 12 | 1.986665 |  |  |

TABLE 4
Optimal feasible solution to the original model excluding the liquidity and earnings per share constraints

| Banks | $x_{1}$ | $f(x)$ | $g(x)$ | $Z=\frac{f(x)}{g(x)}$ |
| :---: | :---: | :---: | :---: | :---: |
| 1 | 0.398615 | 0.02187 | 0.001199 | 18.2402 |
| 2 | 0 |  |  |  |
| 3 | 0 |  |  |  |
| 4 | 0 |  |  |  |
| 5 | 0 |  |  |  |
| 6 | 0.004154 |  |  |  |
| 7 | 0 |  |  |  |
| 8 | 0.244353 |  |  |  |
| 9 | 0.298921 |  |  |  |
| 10 | 0.003103 |  |  |  |
| 11 | 0.007404 |  |  |  |
| 12 | 0.043449 |  |  |  |

TABLE 5
Table of values for the trade-off curve method

| Return | Risk |
| :---: | :---: |
| 0.013 | 0.0013 |
| 0.02 | 0.002 |
| 0.022 | 0.0024 |
| 0.025 | 0.003219 |
| 0.028 | 0.004282 |
| 0.03 | 0.0052 |
| 0.035 | 0.009375 |
| 0.037 | 0.012223 |
| 0.04 | 0.034 |



FIGURE 1: Trade off curve of risks versus returns

### 5.0 Conclusion

The portfolio selection model was formulated as a concave-convex fractional programming problem as shown in equation (10).The model was transformed into a concave quadratic programming problem and solved by the Frank Wolfe's modified algorithm in excel solver.

The optimal solution as shown in Table 2 determines the proportion of investments to be made by an investor in each bank in order to maximize the expected return at minimum risk. The second model without the liquidity and earnings per share constraint as shown in equation (30), indicated the same result in the analysis as the first model which shows that those two constraints are redundant. The trade-off curve as shown in fig 1, indicates the amount of risk to be taken for a particular expected return. Based on the solution of the analysis as shown in table 2 and table 4, it is seen that $x_{2}=x_{3}=x_{4}=x_{5}=x_{7}=0$, which implies that it is risky to invests in those Banks. It is safe for the investors to invest in each portfolio in the following proportion respectively: Bank A $39.86 \%$, Bank F $0.44 \%$, Bank H $24.44 \%$, Bank I $29.91 \%$,

Bank J $0.31 \%$, BANK K $0.73 \%$ and Bank L $4.35 \%$. The computational results show that the proposed model can generate a favourite portfolio strategy according to the investor's satisfactory degree. The trade-off curve also indicates the amount of risk that is commensurate with a particular expected return.

## REFERENCES

Abdulrahim, Basiya K. (2014), On complementary quadratic fractional programming problem. International journal of Applied Mathematical Research, 3 (3), 348-352.
Bisoi S., Devi G., Rath A. (2011) Neural networks for nonlinear fractional programming. Intern J SciEng Res 2 (12): 1-5

Bitran, G. R. and Novaes, A. G. (1972).Linear programming with a fractional objective function.Operations Research, 21 (1), pp 22-29.
Charnes, A \& Cooper, w. W.(1973) "An explicit general solution in linear fractional programming.Nava Research Logistics, vol20, no 3, pps 449-4
.Hasan, M. B. and Acharjee, S. (2011). Solving LFP by converting it into a single LP.International Journal of Operation Research, vol 8, no 3, pp 1-14.
Jain, S. and Lachhwani, K. (2008). Sum of linear and fractional multi-objective programming problem under fuzzy rules constraints. Australian Journal of Basic and Applied Sciences 2, (4), 1204-1208.
Jain, s., Mangal, A. and Sharma, S. (2013). C-approach of ABC algorithm for fractional programming problem.Journal of Computer and Mathematical Sciences,vol 4, no 2, pp 126-134.
Lokhande, K. G.; Khobragade, N. W. and Khot, P. G.(2013). Alternative Approach to linear fractional programming.International Journal of Engineering and Innovative Technology (IJEIT), vol 3
Mehrjerdi, Y. Z (2010). Solving fractional programming problem through fuzzy goal setting and approximation. Applied Soft Computing II, 1735-1742, www.elsevier.com./locate/asoc
Narayanamoorthy, S. and Kalyani, S. (2015).The Intelligence of Dual Simplex Method to Solve Linear Fractional Fuzzy Transportation Problem.
Nigeria Stock Exchange 2015 Annual report and financial statements.www.nigerianstockexchange.com
Pandian, P. and Jayalakshmi, M.(2013).On solving linear fractional programming problems. Modern Applied Sciences, vol 7, no 6, pp 90-100.
Schaible, S. and Jainming Shi (2000); Recent developments in fractional Programming: Single ratio and MaxMin case.www.elsevier.com/locate/ins
Schaible, S.(1981); Fractional programming: Applications and algorithms. European Journal of Operation Research,7, 2, (111-120).
Sharma, S. C. and Bansal, A.(2011).An integer solution of fractional programming problem. General Mathematics Notes, vol 4, no 2, pp 1-9.
Shen P., Ma Y., Chen Y. (2009), Solving sum of quadratic ratios fractional programs via monotonic functions. Appl Math Comput 212(1): 234-244
Singh, H. C. (1981). Optimal Condition in the fractional programming.Journal of Optimization theory and Applications, vol no 33, pp287-294.
Sulaiman, A. and Basiya, K. (2013). Using transformation technique to solve multi-objectivelinear fractional problem. International journal of Research and Reviews in Applied Sciences, vol 14, no 3, pp 559-567.
Tantawy, S. F. (2008); A new procedure for solving linear fractional programming problems .Mathematical and Computer Modelling 48(2008) 969-973. www.elsavier.com/locate/mem
Tantawy,S F. (2011); A new method for solving linear fractional programming problems. Australian Journal of Basic \& Applied Sciences, vol 1, no 2, pp 105-108
Verna, S., Bakhshi, H. C. and Puri, M. C. (1990);.Ranking in integer linear fractional programming problems. ZOR Methods and Models of Operational Research, vol 34, no 5, pp 325-334.
Wayne L. Winston (1994); Operations Research: Applications and Algorithms. An imprint of Wadsworth Publishing Company, Belmont, Califonia 94002

Wagner, H. M. \& Yuan, J. S. C. (1968), Algorithmic equivalence in linear fractional programming. Management Science, 14(5), 301-106
Xiao L. (2010) Neural network method for solving linear fractional programming. International Conference on Computational Intelligence and Security (CIS) (2010), pp 37-41.

