



On the Extended Finite Fourier Transform of a Firmly Fixed Continuously Time Series with Missing Data

By

Dr. Amira Ibrahim. El-Desokey

Lecturer at Higher Future
Institute for Specialized
Technological Studies

aeldesokey@gmail.com

Ali Mohammed Ben Aros

Department of Statistics, Faculty
of Science, Damietta University,
Faculty of Science, Almergib
University, Libya

Dr. Mohammed Abou El-Fettouh Ghazal

Professor of Mathematics
Faculty of Science, Damietta University

APA Citation

El-Desokey, A.I.; Ben Aros, M. A. and Ghazal, M. A. (2023). On the Extended Finite Fourier Transform of a Firmly Fixed Continuously Time Series with Missing Data, *Scientific Journal for Financial and Commercial Studies and Research*, Faculty of Commerce, Damietta University, 4(2), 643-659.

Website: <https://cfdj.journals.ekb.eg/>

Dr. Amira El-Desokey; Ali Ben Aros and Dr. Mohamed Ghazal

On the Extended Finite Fourier Transform of a Firmly Fixed Continuously Time Series with Missing Data

Dr. Amira El-Desokey; Ali. Ben Aros and Dr. Mohammed Ghazal

Abstract- This paper investigates the properties of the extended finite Fourier transform of the firmly fixed of two vector-valued continuously time series. In their own terms, both time series can be conceived of as continuous. Both of the different time series have the property of having a continuous advance throughout their entire. The two relevant time series both have the attribute of a continuous progression throughout their data. This is one of the characteristics that allow them to be flexible. The extended finite Fourier transform provides the basis for the investigations while these characteristics is studied using the framework that it provides. Following that, a data analysis is carried out, during which time both regular and irregular repeating patterns are searched for and examined. This happens while the analysis is being carried out. This process immediately follows the phase in which the data was obtained. This is done simultaneously with data analysis, so the two operations are parallel.

Keywords: Finite Fourier transforms, Missing Data, Data Window, continuously fixed time series, Wishart Distribution.

1. INTRODUCTION

THE extended finite Fourier transform discussed with many authors such that, Brillinger,[1],[2], Dahlhaus,[3], Elhassanein, [4], [5], Farag, and Ghazal[6], [7], Ghazal,[8], Ghazal et al., [9], [10], [11], [15], [16], Ghazal, and Elhassanin, [12], Ghazal, and Farag, [13], [14], Mokkadis, et al., [17]. This paper is organized as follow, Section 1, Introduction, the statistical analysis of the extended finite continuous Fourier transform with observed data (regular pattern) will discussed in Sec.2, in Sec. 3, we will study the extended finite continuous Fourier Transform with missing observations (irregular pattern), and in Sec. 4, the characteristics of the extended continuous finite Fourier transform in irregular patterns will be discussed. In section 5, we discussed the practical implications of our theoretical research for the Arab Cement Factory, focusing on the company's monthly production and quantity of concrete sales from January 2010 to December 2015.

2. THE STATISTICAL ANALYSIS OF THE EXTENDED FINITE CONTINUOUS FOURIER TRANSFORM WITH OBSERVED DATA (REGULAR PATTERN)

Let $(s + r)$ be a two vector-valued fixed continuous time series

$$\beta(t) = \begin{bmatrix} X(t) \\ \tau(t) \end{bmatrix}, \quad (2.1)$$

$t = 0, \pm 1, \pm 2, \dots$, With $X(t)$, s vector-valued and $\tau(t)$, r vector-valued a firmly fixed $(s + r)$ vector-valued series with components,

$$\begin{bmatrix} X_j(t) \\ \tau_i(t) \end{bmatrix}, j = 1, 2, \dots, s, i = 1, 2, \dots, r,$$

where moments exist, then the mean is defined as

$$EX(t) = 0, E\tau(t) = 0, \quad (2.2)$$

The covariances are given by

$$\begin{aligned} E\{[X(t+h) - \ell_x][X(t) - \ell_x]^T\} &= \ell_{xx}(h), \\ E\{[X(t+h) - \ell_x][\tau(t) - \ell_\tau]^T\} &= \ell_{x\tau}(h), \\ E\{[\tau(t+h) - \ell_\tau][\tau(t) - \ell_\tau]^T\} &= \ell_{\tau\tau}(h), \end{aligned} \quad (2.3)$$

with spectral densities:

Dr. Amira El-Desokey; Ali Ben Aros and Dr. Mohamed Ghazal

$$\begin{aligned}
 f_{xx}(d) &= (2\pi)^{-1} \int_{-\infty}^{\infty} \ell_{xx}(h) \text{Exp}(-idh) dh \\
 f_{x\tau}(d) &= (2\pi)^{-1} \int_{-\infty}^{\infty} \ell_{x\tau}(h) \text{Exp}(-idh) dh, \text{ for } d \\
 &\in R \\
 f_{\tau\tau}(d) &= (2\pi)^{-1} \int_{-\infty}^{\infty} \ell_{\tau\tau}(h) \text{Exp}(-idh) dh
 \end{aligned}
 \tag{2.4}$$

Let $\phi_a(t), a = 1, 2, \dots, s, (t \in R)$ be an independent series of $\beta(t)$ such that every t ,

$$\begin{aligned}
 P[\phi_a(t) = 1] &= p_a, \\
 P[\phi_a(t) = 0] &= q_a
 \end{aligned}
 \tag{2.5}$$

and,

$$E\{\phi_a(t)\} = P, \tag{2.6}$$

Then we can define the altered continuous series as

$$Z(t) = \phi(t)\beta(t), \tag{2.7}$$

Where,

$$Z_a(t) = \phi_a(t)\beta_a(t), \tag{2.8}$$

Assumption I. Let $\lambda_a^{(T)}(t)$ be a variation that is constrained and vanishes $0 < t < T - 1$. Which is known as the data window and satisfies

$$\begin{aligned}
 \frac{1}{T} \int_0^T \lambda_a^{(T)}(t) dt &\xrightarrow{T \rightarrow \infty} \int_0^1 \lambda_a(h) dh, a = \overline{1, s} \\
 \alpha^{(T)}_{a_1, \dots, a_k}(d) &= \int_0^T \left[\prod_{j=1}^M \lambda_{a_j}^{(T)}(t) \right] \text{Exp}\{-idt\} dt
 \end{aligned}$$

Use an r -vector, \underline{G} , and $r \times s$ filter $\{b(h)\}$, so

$$\tau(t) \approx \underline{G} + \sum_{h=-\infty}^{\infty} b(t-h)X(h), \tag{2.9}$$

Using Hermitian matrix then

$$E\{[\tau(t) - \underline{G} - \sum_{h=-\infty}^{\infty} b(t-h)X(h)][\tau(t) - \underline{G} - \sum_{h=-\infty}^{\infty} b(t-h)X(h)]^T\}, \tag{2.10}$$

Theorem 2.1. [2]. Supposing $f_{xx}(d)$ given by (2.4), which is nonsingular, and $d \in \mathbb{R}$. for a $(s + r)$ vector-valued of Second-order fixed continuous time series with mean (2.2) and autocovariance function (2.3). Following this, the values of, \underline{G} , and $b(h)$ that minimize (2.10) are provided

$$\underline{G} = \ell_\tau - \left(\sum_{h=-\infty}^{\infty} b(h) \right) \ell_x = \ell_\tau - H(0)\ell_x, \quad (2.11)$$

and

$$b(h) = (2\pi)^{-1} \int_0^{2\pi} H(a) \text{Exp}\{iha\} da, \quad (2.12)$$

where,

$$H(d) = f_{\tau x}(d) f_{xx}(d)^{-1}, \quad (2.13)$$

The filter $\{b(h)\}$ is absolutely summable. The minimum achieved is

$$\int_0^{2\pi} [f_{\tau\tau}(a) - f_{\tau x}(a) f_{xx}(a)^{-1} f_{x\tau}(a)] da, \quad (2.14)$$

3. The Extended Finite CONTINUOUS Fourier Transform with Missing Observations (Irregular Pattern)

Theorem 3.1. Let $Z_a(t) = \phi_a(t)\beta_a(t)$, $a = 1, 2, \dots, \min(s, r)$, are stochastic fixed continuous process with missing observations, $X_a(t)$, $\tau_a(t)$, $a = 1, 2, \dots, \min(s, r)$ and $\phi_a(t)$ is Bernoulli Sequences and satisfies (2.8), then,

$$E\{Z_a(t)\} = 0, \quad (3.1)$$

$$\text{Cov}\{Z_{a_1}(t_1), Z_{a_2}(t_2)\} = \begin{bmatrix} P_{a_1 a_2} \ell_{xx}(h) & P_{a_1 a_2} \ell_{xx}(h) H(d)^T \\ P_{a_1 a_2} H(d) \ell_{xx}(h) & P_{a_1 a_2} H(d) \ell_{xx}(h) H(d)^T \end{bmatrix}, \quad (3.2)$$

Proof.

From the independence of $\beta_a(t)$ and $\phi_a(t)$, then (3.1) is obtained directly.

Now we have,

$$\text{Cov}\{Z_{a_1}(t_1), Z_{a_2}(t_2)\} = \text{Cov}\{\phi_{a_1}(t)\beta_{a_1}(t), \phi_{a_2}(t)\beta_{a_2}(t)\}$$

$$\begin{aligned}
 &= Cov \left\{ \begin{bmatrix} \phi_{a_1}(t_1)X_{a_1}(t_1) \\ \phi_{a_1}(t_1)\tau_{a_1}(t_1) \end{bmatrix}, \begin{bmatrix} \phi_{a_2}(t_2)X_{a_2}(t_2) \\ \phi_{a_2}(t_2)\tau_{a_2}(t_2) \end{bmatrix}^T \right\} = \\
 &E \begin{bmatrix} \phi_{a_1}(t_1)X_{a_1}(t_1)\phi_{a_2}(t_2)X_{a_2}(t_2) & \phi_{a_1}(t_1)X_{a_1}(t_1)\phi_{a_2}(t_2)\tau_{a_2}(t_2) \\ \phi_{a_1}(t_1)\tau_{a_1}(t_1)\phi_{a_2}(t_2)X_{a_2}(t_2) & \phi_{a_1}(t_1)\tau_{a_1}(t_1)\phi_{a_2}(t_2)\tau_{a_2}(t_2) \end{bmatrix} \\
 &= \begin{bmatrix} E[\phi_{a_1}(t_1)\phi_{a_2}(t_2)]Cov[X_{a_1}(t_1), X_{a_2}(t_2)] & E[\phi_{a_1}(t_1)\phi_{a_2}(t_2)]Cov[X_{a_1}(t_1), \tau_{a_2}(t_2)] \\ E[\phi_{a_1}(t_1)\phi_{a_2}(t_2)]Cov[\tau_{a_1}(t_1), X_{a_2}(t_2)] & E[\phi_{a_1}(t_1)\phi_{a_2}(t_2)]Cov[\tau_{a_1}(t_1), \tau_{a_2}(t_2)] \end{bmatrix} \\
 &= \begin{bmatrix} P_{a_1 a_2} Cov[X_{a_1}(t_1), X_{a_2}(t_2)] & P_{a_1 a_2} Cov[X_{a_1}(t_1), G + H(a)X_{a_2}(t_2)] \\ P_{a_1 a_2} Cov[G + H(a)X_{a_1}(t_1), X_{a_2}(t_2)] & P_{a_1 a_2} Cov[G + H(a)X_{a_1}(t_1), G + H(a)X_{a_2}(t_2)] \end{bmatrix}
 \end{aligned}$$

From (2.3) we have,

$$Cov\{Z_{a_1}(t_1), Z_{a_2}(t_2)\} = \begin{bmatrix} P_{a_1 a_2} \ell_{xx}(h) & P_{a_1 a_2} \ell_{xx}(h)H(d)^T \\ P_{a_1 a_2} H(d)\ell_{xx}(h) & P_{a_1 a_2} H(d)\ell_{xx}(h)H(d)^T \end{bmatrix}$$

Then (3.2) is obtained.

Definition: The Wishart Distribution [2], [89-90].

Assume that X and τ are independent random vectors in R_k , and that $Vec [X \ \tau]$ is a normal vector of dimension $2k$. If this is the case, then the Wishart distribution holds for the complex random vector $\Psi = X + i\tau$. Three parameters, $\underline{G} = E(\psi)$, $\theta = E[(\psi - G)(\bar{\psi} - \bar{G})^T]$, and $\ell = E[(\psi - G)(\psi - G)^T]$ characterize this distribution, where ψ^T denotes matrix transpose and signifies complex conjugate. Here, G can be any k -dimensional complex vector, must be Hermitian and non-negative definite, and ℓ should be a symmetric matrix. Moreover, matrices θ and ℓ are such that the matrix $\bar{\theta} - \bar{\ell}^T \theta^{-1} \ell$ is also non-negative definite and the matrices θ and ℓ are related to the covariance matrices of X and τ .

Theorem 3.2. Let $Z_a(t) = \phi_a(t)\beta_a(t)$, $a = 1, 2, \dots, \min(s, r)$ are stochastic fixed continuous process with missing observations $X_a(t), \tau_a(t)$, $a = 1, 2, \dots, \min(s, r)$ and $\phi_a(t)$ is Bernoulli sequence and satisfies (2.8), and $\lambda_a^{(T)}(t)$ satisfies Assumption I, then the continuously extended finite Fourier transform can be defined as

$$\gamma_a^{(T)}(d) = \left[2\pi \int_0^T (\lambda_a^{(T)}(t))^2 \right]^{-1/2} \int_{-\infty}^{\infty} \lambda_a^{(T)}(t) Z_a(t) \exp\{-idt\} dt, \text{ for } d \in R \tag{3.3}$$

Dr. Amira El-Desokey; Ali Ben Aros and Dr. Mohamed Ghazal

Which is distributed approximately as Wishart distribution (Complex normal distribution) as

$$N_{s+r}^c \left(\underline{0}, \begin{bmatrix} V_1 & V_2 \\ V_3 & V_4 \end{bmatrix} \right), \quad (3.4)$$

Where,

$$\begin{aligned} v_1 &= P_{a_1 a_2} \int_{\mathbb{R}} f_{a_1 a_2}(u) \Omega_{a_1 a_2}^{(T)}(d_1 - u, d_2 - u) du, \\ v_2 &= P_{a_1 a_2} \int_{\mathbb{R}} f_{a_1 a_2}(u) H(d)^T \Omega_{a_1 a_2}^{(T)}(d_1 - u, d_2 - u) du, \\ v_3 &= P_{a_1 a_2} \int_{\mathbb{R}} H(d) f_{a_1 a_2}(u) \Omega_{a_1 a_2}^{(T)}(d_1 - u, d_2 - u) du, \\ v_4 &= P_{a_1 a_2} \int_{\mathbb{R}} H(d) f_{a_1 a_2}(u) H(d)^T \Omega_{a_1 a_2}^{(T)}(d_1 - u, d_2 - u) du, \end{aligned}$$

Proof.

To prove theorem (3.2), first we have to prove that

$$E\{\gamma_a(t)\} = 0,$$

Which comes directly using (3.1) and (3.3).

Now we have,

$$\begin{aligned} Cov\{\gamma_{a_1}^{(T)}(d_1), \gamma_{a_2}^{(T)}(d_2)\} &= E\left\{\gamma_{a_1}^{(T)}(d_1) \overline{\gamma_{a_2}^{(T)}(d_2)}\right\} \\ &= (2\pi)^{-1} \left[\int_{t_1=0}^T \int_{t_2=0}^T (\lambda_{a_1}^{(T)}(t_1))^2 (\lambda_{a_2}^{(T)}(t_2))^2 dt_1 dt_2 \right]^{-1/2} \times \\ &\times \int_{t_1=0}^T \int_{t_2=0}^T \lambda_{a_1}(t_1) \lambda_{a_2}(t_2) Cov(Z_{a_1}(t_1), Z_{a_2}(t_2)) \exp(-i(t_1 d_1 \\ &\quad - t_2 d_2)) dt_1 dt_2 \end{aligned}$$

Using theorem (3.1), equation (3.2) then

$$\begin{aligned} Cov\{\gamma_{a_1}^{(T)}(d_1), \gamma_{a_2}^{(T)}(d_2)\} &= (2\pi)^{-1} \left[\int_{t_1=0}^T \int_{t_2=0}^T (\lambda_{a_1}^{(T)}(t_1))^2 (\lambda_{a_2}^{(T)}(t_2))^2 \right]^{-1/2} \times \\ &\times \int_{t_1=0}^T \int_{t_2=0}^T \lambda_{a_1}(t_1) \lambda_{a_2}(t_2) \exp(-i(t_1 d_1 - t_2 d_2)) dt_1 dt_2 \times \\ &\times \begin{bmatrix} P_{a_1 a_2} \ell_{xx}(t_1 - t_2) & P_{a_1 a_2} \ell_{xx}(t_1 - t_2) H(d)^T \\ P_{a_1 a_2} H(d) \ell_{xx}(t_1 - t_2) & P_{a_1 a_2} H(d) \ell_{xx}(t_1 - t_2) H(d)^T \end{bmatrix} \end{aligned} \quad (3.4)$$

substituting $t_1 - t_2 = h, t_2 = t$, then we have,

$$\begin{aligned} \text{Cov}\{\gamma_{a_1}^{(T)}(d_1), \gamma_{a_2}^{(T)}(d_2)\} &= \\ &= (2\pi)^{-1} \left[\int_{t_1=0}^T \int_{t_2=0}^T (\lambda_{a_1}^{(T)}(t_1))^2 (\lambda_{a_2}^{(T)}(t_2))^2 dt_1 dt_2 \right]^{-1/2} \times \\ &\times \int_{t_1=-T}^T \int_{t_2=0}^T \lambda_{a_1}(t+h) \lambda_{a_2}(t) \exp(-it(d_1 - d_2)) dt dh \times \\ &\times \\ &\begin{bmatrix} P_{a_1 a_2} \ell_{xx}(h) & P_{a_1 a_2} \ell_{xx}(h) H(d)^T \\ P_{a_1 a_2} H(d) \ell_{xx}(h) & P_{a_1 a_2} H(d) \ell_{xx}(h) H(d)^T \end{bmatrix}, \end{aligned} \tag{3.5}$$

$$= \begin{bmatrix} P_{a_1 a_2} \ell_{xx}(h) & P_{a_1 a_2} \ell_{xx}(h) H(d)^T \\ P_{a_1 a_2} H(d) \ell_{xx}(h) & P_{a_1 a_2} H(d) \ell_{xx}(h) H(d)^T \end{bmatrix} = \begin{bmatrix} v_1 & v_2 \\ v_3 & v_4 \end{bmatrix}, \tag{3.6}$$

where,

$$\ell_{xx}(h) = E\{X(t+h)X(t)\} = \int_{-\infty}^{\infty} f_{xx}(d) \exp(idh), \tag{3.7}$$

Substituting (3.7) into (3.5) we have,

$$\begin{aligned} v_1 &= p_{a_1 a_2} \int_{-\infty}^{\infty} f_{a_1 a_2}(u) (2\pi)^{-1} \left[\int_{t_1=0}^T \int_{t_2=0}^T (\lambda_{a_1}^{(T)}(t_1))^2 (\lambda_{a_2}^{(T)}(t_2))^2 dt_1 dt_2 \right]^{-1/2} \times \\ &\times \left\{ \int_{t_1=0}^T \int_{t_2=0}^T \lambda_{a_1}(t_1) \lambda_{a_2}(t_2) \exp(-i[(d_1 - u)t_1 - (d_2 - u)t_2]) dt_1 dt_2 \right\} du, \\ v_1 &= p_{a_1 a_2} \int_{-\infty}^{\infty} f_{a_1 a_2}(u) \Omega_{a_1 a_2}(d_1 - u, d_2 - u) du, \end{aligned}$$

Where,

$$\begin{aligned} \Omega_{a_1 a_2}(d_1 - u, d_2 - u) &= \\ &(2\pi)^{-1} \left[\int_{t_1=0}^T \int_{t_2=0}^T (\lambda_{a_1}^{(T)}(t_1))^2 (\lambda_{a_2}^{(T)}(t_2))^2 dt_1 dt_2 \right]^{-1/2} \times \\ &\times \left\{ \int_{t_1=-T}^T \int_{t_2=0}^T \lambda_{a_1}^{(T)}(t+h) \lambda_{a_2}^{(T)}(t_2) \exp(-i[(d_1 - u)t - (d_2 - u)t]) dt du \right\}, \end{aligned}$$

Also

$$\begin{aligned} v_2 &= p_{a_1 a_2} \int_{-\infty}^{\infty} f_{a_1 a_2}(u) H(d)^T \Omega_{a_1 a_2}(d_1 - u, d_2 - u) du, \\ v_3 &= p_{a_1 a_2} \int_{-\infty}^{\infty} H(d) f_{a_1 a_2}(u) \Omega_{a_1 a_2}(d_1 - u, d_2 - u) du, \\ v_4 &= p_{a_1 a_2} \int_{-\infty}^{\infty} H(d) f_{a_1 a_2}(u) H(d)^T \Omega_{a_1 a_2}(d_1 - u, d_2 - u) du, \end{aligned}$$

Then the theorem is proved.

4. THE CHARACTERISTICS OF THE EXTENDED FINITE CONTINUOUS FOURIER TRANSFORM IN IRREGULAR PATTERN

Lemma 4.1. Since (3.3) defines $\gamma_a^{(T)}(d), a = 1, \dots, \min(r, s)$, as the distribution function, we have that the dispersion of $\gamma_a^{(T)}(d)$ meets the following.

$$D\gamma_a^{(T)}(d) = P_{aa} \left[\begin{array}{cc} \int_{-\infty}^{\infty} f_{aa}(d-v) \Omega_{aa}(v) dv & \int_{-\infty}^{\infty} f_{aa}(d-v) H(d)^T \Omega_{aa}(v) dv \\ \int_{-\infty}^{\infty} H(d) f_{aa}(d-v) \Omega_{aa}(v) dv & \int_{-\infty}^{\infty} H(d) f_{aa}(d-v) H(d)^T \Omega_{aa}(v) dv \end{array} \right], \quad (4.1)$$

Lemma 4.2. Let $\lambda_a^{(T)}(t), t \in R, a = 1, \dots, \min(s, r)$ is bounded by a constant N and satisfying

$$|\lambda_a^{(T)}(t+h) - \lambda_a^{(T)}(t)| \leq L|h|,$$

Then,

$$\left| \int_0^T \lambda_{a_1}^{(T)}(t) \lambda_{a_2}^{(T)}(t) \exp(-idt) dt \right| \leq \frac{1}{|d|} + NL, \quad (4.2)$$

For some constants N, L and, $d \in R, d \neq 0, a_1, a_2 = 1, \dots, \min(s, r)$.

Lemma 4.3. For $d_1 - d_2 \neq 0, d_1, d_2 \in R$ and $\lambda_a^{(T)}(t), t \in R, a = 1, \dots, \min(s, r)$ is bounded by constant N and satisfying (4.2), then,

$$\begin{aligned} & |Cov\{\gamma_{a_1}^{(T)}(d_1), \gamma_{a_2}^{(T)}(d_2)\}| \leq \\ & \leq \frac{NL}{2\pi \sqrt{\int_0^T \int_0^T (\lambda_{a_1}^{(T)}(t_1))^2 (\lambda_{a_2}^{(T)}(t_2))^2 dt_1 dt_2}} \times \\ & \times \left\{ \frac{1}{NL|(d_1 - d_2)/2|} \int_{-T}^T |\ell_{a_1 a_2}(h)| dh + \int_{-T}^T |\ell_{a_1 a_2}(h)| [|h| + 1] dh \right\}, \end{aligned} \quad (4.3)$$

For $a_1, a_2 = 1, \dots, \min(s, r)$.

Theorem 4.1. For $d_1 - d_2 \neq 0, d_1, d_2 \in R$ and $\lambda_a^{(T)}(t), t \in R, a = 1, \dots, \min(s, r)$ is bounded by constant N and satisfying (4.2) and,

$$\int_{-\infty}^{\infty} [|h| + 1] |\ell_{a_1 a_2}(h)| dh < \infty,$$

then,

$$\lim_{T \rightarrow \infty} \text{Cov}\{\gamma_{a_1}^{(T)}(d_1), \gamma_{a_2}^{(T)}(d_2)\} = 0,$$

For all $a_1, a_2 = 1, \dots, \min(s, r)$.

Proof.

Assumption I and Lemma (4.3) provide the foundation for the proof.

Theorem 4.2. For any $d \in \mathbb{R}$, the function $\Omega_{aa}^{(T)}(d)$, $a = 1, \dots, \min(s, r)$ is the Kernel that satisfies the following characteristics:

$$(1) \int_{-\infty}^{\infty} \Omega_{aa}^{(T)}(d) dd = 1, a = 1, \dots, \min(s, r), \tag{4.4}$$

$$(2) \lim_{T \rightarrow \infty} \int_{-\infty}^{-\theta} \Omega_{aa}^{(T)}(d) dd = \lim_{T \rightarrow \infty} \int_{\theta}^{\infty} \Omega_{aa}^{(T)}(d) dd = 0, \tag{4.5}$$

For $\theta > 0, a = 1, \dots, \min(s, r), d \in \mathbb{R},$

$$(3) \lim_{T \rightarrow \infty} \int_{-\theta}^{\theta} \Omega_{aa}^{(T)}(d) dd = 1, \tag{4.6}$$

for all $\theta > 0, a = 1, \dots, \min(s, r), d \in \mathbb{R}.$

Theorem 4.3. For the function $\Omega_{aa}^{(T)}(x)$, $a = 1, \dots, \min(s, r), x \in \mathbb{R}$, that satisfies the characteristics of the theorem (4.2), and if the spectral density function $f_{aa}(x)$, $a = 1, \dots, \min(s, r), x \in \mathbb{R}$ is bounded and continuously at a point $x = d, d \in \mathbb{R}$, then

$$\lim_{T \rightarrow \infty} D\gamma_a^{(T)}(d) = \begin{bmatrix} f_{aa}(d) & f_{aa}(d)H(a)^T \\ H(a)f_{aa}(d) & H(a)^T f_{aa}(d)H(a) \end{bmatrix} \xrightarrow{T \rightarrow \infty} 0, \tag{4.7}$$

$a = 1, \dots, \min(s, r),$

5. Application Study

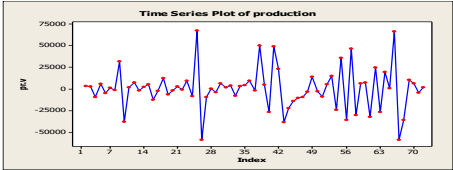

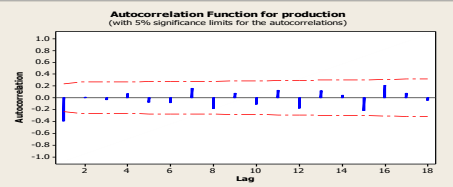
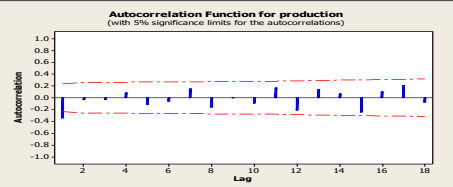
We discuss the practical implications of our theoretical research for the Arab Cement Factory, focusing on the company's monthly production and quantity of concrete sales from January 2010 to December 2015.

5.1.1. Analyzing the Production.

Our results, obtained from a model of firmly fixed time series with some missing observations, will be compared with the classical results, obtained when all observations are present, in this investigation.

Let $\eta_a(t) = \varphi_a(t)X_a(t)$, $a = 1, 2, \dots, r$, where $X_a(t)$, $(t = 0, \pm 1, \dots)$ is a firmly fixed s-vector valued time series, and $\varphi_a(t)$ is a Bernoulli sequence of stochastically independent random variables be stochastically independent of $X_a(t)$. We assume that the data $X_a(t)$, $(t = (1, 2, \dots, T])$, which is the average of the monthly production for which all observations are available, is available with some missing observations, $\varphi = 1$, $\eta_a(t) = X_a(t)$, The table (5.1.1) compares the results with and without missing observations, assuming that some observations are randomly missing $\varphi_a(t) = 0$ in the classical scenario.

Table (5.1.1) Analysis of Production Data with and without Missing data.

without missing data	with missing data
 <p>The monthly average production</p>	 <p>The monthly average production</p>
 <p>ACF of the monthly average production</p>	 <p>ACF of the monthly average production</p>

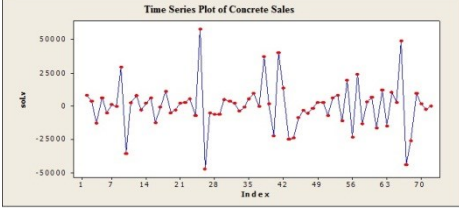
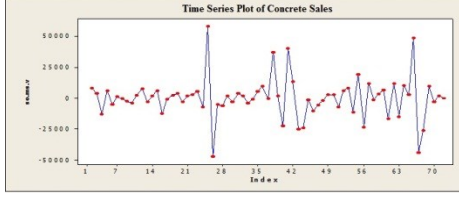
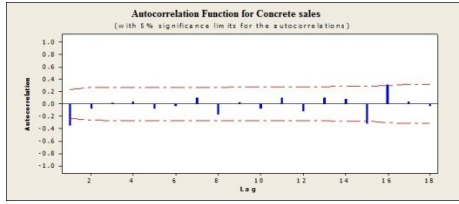
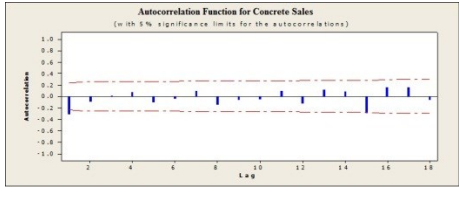
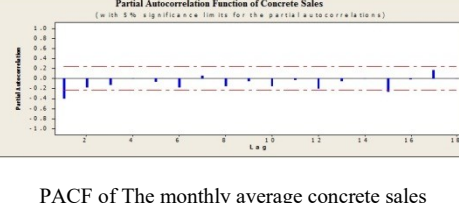
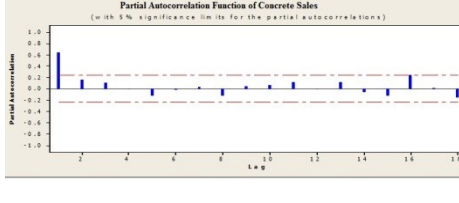
PACF of the monthly average production						PACF of the monthly average production					
ARIMA(1,1,1)						ARIMA(1,1,1)					
Final Parameters Estimates						Final Parameters Estimates					
Type	Coef	SE Coef	T	P		Type	Coef	SE Coef	T	P	
AR 1	0.6013	0.0987	4.39	0.000		AR 1	0.6684	0.1124	5.01	0.000	
MA 1	0.968	0.0523	20.89	0.000		MA 1	0.9678	0.0519	21.53	0.000	
Residuals: SS = 299874459104 (back forecasts excluded)						Residuals: SS = 297761014349 (back forecasts excluded)					
MS = 43459707, DF = 68						MS = 367970146, DF = 68					
Modified Box-Pierce (Ljung-Box) Chi-Square statistic						Modified Box-Pierce (Ljung-Box) Chi-Square statistic					
Lag	12	24	36	48		Lag	12	24	36	48	
Chi-Square	11.4	21.6	37.6	49.7		Chi-Square	11.3	23.5	40.5	524	
DF	9	21	33	45		DF	9	21	33	45	
P-Value	0.240	0.414	0.262	0.288		P-Value	0.251	0.314	0.168	0.205	

5.1.2. Analysis of concrete sales

Our results, obtained from a model of firmly fixed time series with some missing observations, will be compared with the classical results, obtained when all observations are present, in this investigation.

Let $\eta_a(t) = \varphi_a(t)X_a(t)$, $a = 1, 2, \dots, r$, where $X_a(t)$, $(t = 0, \pm 1, \dots)$ is a firmly fixed s-vector valued time series, and $\varphi_a(t)$ is a Bernoulli sequence of stochastically independent random variables be stochastically independent of $X_a(t)$. We assume that the data $X_a(t)$, $(t = (1, 2, \dots, T])$, which is the average of the monthly concrete sales for which all observations are available, is available with some missing observations, $\varphi = 1$, $\eta_a(t) = X_a(t)$. The table (5.1.2) compares the results with and without missing observations, assuming that some observations are randomly missing $\varphi_a(t) = 0$ in the classical scenario.

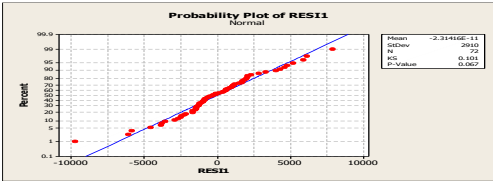
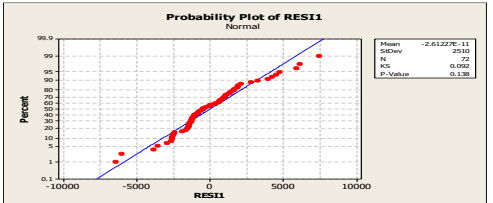
Table (5.1.2) Analysis of concrete sales with and without missing data

without missing data	with missing data																																																																						
 <p>The monthly average concrete sales</p>	 <p>The monthly average concrete sales</p>																																																																						
 <p>ACF The monthly average concrete sales</p>	 <p>ACF of The monthly average concrete sales</p>																																																																						
 <p>PACF of The monthly average concrete sales</p>	 <p>PACF of The monthly average concrete sales</p>																																																																						
<p>ARIMA(1,1,1)</p> <p>Final Estimates of Parameters</p> <table border="1"> <thead> <tr> <th>Type</th> <th>Coef</th> <th>SE Coef</th> <th>T</th> <th>P</th> </tr> </thead> <tbody> <tr> <td>AR 1</td> <td>0.5185</td> <td>0.1081</td> <td>4.75</td> <td>0.000</td> </tr> <tr> <td>AM 1</td> <td>0.9826</td> <td>0.0524</td> <td>21.06</td> <td>0.000</td> </tr> </tbody> </table> <p>Residuals: SS = 18165211322 (back forecasts excluded) MS = 224782472, DF = 68 Modified Box-Pierce (Ljung-Box) Chi-Square statistic</p> <table border="1"> <thead> <tr> <th>Lag</th> <th>12</th> <th>24</th> <th>36</th> <th>48</th> </tr> </thead> <tbody> <tr> <td>Chi-Square</td> <td>7.01</td> <td>22</td> <td>37.2</td> <td>50.3</td> </tr> <tr> <td>DF</td> <td>9</td> <td>21</td> <td>33</td> <td>45</td> </tr> <tr> <td>P-Value</td> <td>0.557</td> <td>0.364</td> <td>0.297</td> <td>0.295</td> </tr> </tbody> </table>	Type	Coef	SE Coef	T	P	AR 1	0.5185	0.1081	4.75	0.000	AM 1	0.9826	0.0524	21.06	0.000	Lag	12	24	36	48	Chi-Square	7.01	22	37.2	50.3	DF	9	21	33	45	P-Value	0.557	0.364	0.297	0.295	<p>ARIMA(1,1,1)</p> <p>Final Estimates of Parameters</p> <table border="1"> <thead> <tr> <th>Type</th> <th>Coef</th> <th>SE Coef</th> <th>T</th> <th>P</th> </tr> </thead> <tbody> <tr> <td>AR 1</td> <td>0.5516</td> <td>0.1700</td> <td>5.42</td> <td>0.000</td> </tr> <tr> <td>AM 2</td> <td>0.9376</td> <td>0.0488</td> <td>21.57</td> <td>0.000</td> </tr> </tbody> </table> <p>Residuals: SS = 15881423120 (back forecasts excluded) MS = 232289248, DF = 68 Modified Box-Pierce (Ljung-Box) Chi-Square statistic</p> <table border="1"> <thead> <tr> <th>Lag</th> <th>12</th> <th>24</th> <th>36</th> <th>48</th> </tr> </thead> <tbody> <tr> <td>Chi-Square</td> <td>7.4</td> <td>19.8</td> <td>35.5</td> <td>47.6</td> </tr> <tr> <td>DF</td> <td>9</td> <td>21</td> <td>33</td> <td>45</td> </tr> <tr> <td>P-Value</td> <td>0.641</td> <td>0.562</td> <td>0.384</td> <td>0.326</td> </tr> </tbody> </table>	Type	Coef	SE Coef	T	P	AR 1	0.5516	0.1700	5.42	0.000	AM 2	0.9376	0.0488	21.57	0.000	Lag	12	24	36	48	Chi-Square	7.4	19.8	35.5	47.6	DF	9	21	33	45	P-Value	0.641	0.562	0.384	0.326
Type	Coef	SE Coef	T	P																																																																			
AR 1	0.5185	0.1081	4.75	0.000																																																																			
AM 1	0.9826	0.0524	21.06	0.000																																																																			
Lag	12	24	36	48																																																																			
Chi-Square	7.01	22	37.2	50.3																																																																			
DF	9	21	33	45																																																																			
P-Value	0.557	0.364	0.297	0.295																																																																			
Type	Coef	SE Coef	T	P																																																																			
AR 1	0.5516	0.1700	5.42	0.000																																																																			
AM 2	0.9376	0.0488	21.57	0.000																																																																			
Lag	12	24	36	48																																																																			
Chi-Square	7.4	19.8	35.5	47.6																																																																			
DF	9	21	33	45																																																																			
P-Value	0.641	0.562	0.384	0.326																																																																			

5.1.3. Analysis the Correlation between Concrete Sales and Monthly Production

Now, we turning to compare our results—a regression model between monthly averages of Production and monthly averages of concrete sales with some missing observations—against the classical results, where all observations are available, for the two scenarios indicated in the table below (5.1.3)

Table (5.1.3) Comparing the regression analysis with and without missing data

Without missing data						With missing data					
The regression equation is Concrete Sales = 3633 + 0.773 Production						The regression equation is Concrete Sales = 3322 + 0.734 Production					
Predictor	Coef	SE Coef	T	P		Predictor	Coef	SE Coef	T	P	
Constant	3633	610.2	5.05	0.000		Constant	3322	502.6	5.91	0.000	
Production	0.773	0.01438	54.56	0.000		Production	0.734	0.01027	63.845	0.000	
S = 2813.61 R-Sq = 96.7% R-Sq(adj) = 96.7%						S = 2391.61 R-Sq = 97.9% R-Sq(adj) = 99.9%					
Analysis of Variance						Analysis of Variance					
Source	DF	SS	MS	F	P	Source	DF	SS	MS	F	P
Regression 1	26511160296	26651166902	2985.7	0.000		Regression 1	27655793510	26575791530	4023.66	0.000	
Residual Error	70	640151719	85961	0.000		Residual Error	70	474238847	6893119		
Total	71	27151312015				Total	71	28130032357			
Durbin-watson statistic =1.67188						Durbin-watson statistic =1.67825					
 <p>Normal-graph for standardized Residuals</p>						 <p>Normal-graph for standardized Residuals</p>					

5.1.4. Results and Discussion

(1) No significant differences were found between the findings of studying classical time series and those of studying time series with missing observations.

(2) Similar to the case of missing data, the findings of the studied regression model between classical time series $X(t)$, $\tau(t)$ satisfied all theoretical, mathematical, and least squares constraints.

6. Conclusion

The analysis of the function of the extended finite CONTINUOUS Fourier transform of the firmly fixed Continuously time series in regular patterns is approximately to the analysis of the function of the extended finite Fourier transform of the firmly fixed Continuously time series in irregular pattern.

REFERENCES

- [1] Brillinger D.R., "Asymptotic Characteristics of Spectral Estimates of Second Order, *Biometrika*56 (2), (2001), 375-390.
- [2] Brillinger, D.R., *Time Series Data Analysis and Theory* (2001).
- [3] Dahlhaus, R., "On a Spectral Density Estimate Obtained by Averaging Periodograms", *J. Appl. Probab.* 22, (1985), 592-610.
- [4] ELHASSAIN, A., "Nonparametric Spectral Analysis on Disjoint Segments of Observations", *Journal of the Applied Mathematics, Statistics and Informatics (JAMSI)*, 7 (2011), No.1.
- [5] ELHASSAIN, A., "On the Theory of Continuous Time series", *Indian. Pure Appl. Math*, 45 (3): 297-310, June (2014).
- [6] Farag, E.A., and Ghazal, M. A., "Some Statistical Analysis for Continuous Time Stationary Process With Missed Data", *Since Journal of Mathematics and statistics*, V. 2015, Article ID: Sjms/109, 15 pages, doi: 107237/Sjms/109, 2015.
- [7] Farag, E.A., and Ghazal, M. A., "Some properties of The Function Corresponding To Analysis of Time Series", *Science Journal of Mathematics and Statistics*, V.2016, Article ID: Sjms/112, 6 pages, doi: 10.7237/sjms/112, 2016.
- [8] Ghazal, M. A., "On a Spectral Density Estimate on Non-Crossed Intervals Observation", *Int. J. Appl. Math.* 1(8), (1999), 875-882.
- [9] Ghazal, M. A., El-Desokey , A.E., and Alargt, M. A., "Asymptotic Properties Of The Discrete Stability Time Series With Missed Observations Between Two Vector -Valued Stochastic Process", *International Research Journal of engineering and technology, (IRJET)*, 12, pp. 2052-2063, 2017.
- [10] Ghazal, M. A., El-Desokey , A.E., and Alargt, M. A., "Statistical Properties Of The Periodogram For Two Vector- Valued Stability Series With Missed Observations", *Int. Research Journal of Applied Mathematics and Statistics*, 4, (4), 2017.
- [11] Ghazal, M. A., and El-hassanein, A., "Periodogram Analysis with Missed Observations", *J. Appl. Math. Computing* Vol.22, (2006), No.1-2, pp209-222.
- [12] Ghazal, M. A., and Farag, E.A., "Estimating The Spectral Density, Autocovariance Function And Spectral Measure Of Continuous-Time stationary Processes, in: *Annual Conference*", ISSR, Cairo, Vol.33, no. part, 1998, pp.1-20.

- [13] Ghazal, M. A., and Farag, E.A., "Some properties of The Expanded Finite Fourier Transform", *Statistica*, annoLX, no.3, 2000.
- [14] Ghazal, M. A., Farag, E.A., and EL-Desokey, A.E, "Some properties of the Discrete Expanded finite Fourier transform with missed Observations", Vol.40, No.3, 30 September (2005), pp. 887-902.
- [15] Ghazal, M. A., Mokaddis, G.S., and El-Desokey, , A.E., "Spectral analysis of firmly stationary Continuous time series", *Journal of Mathematical Sciences*, Vol.3, No.1 (2009).
- [16] Mokaddis, G.S., Ghazal, M.A. and El-Desokey, A.E. "Asymptotic Properties of Spectral Estimates of Second-Order with Missed Observations", *Journal of Mathematics and statistics* 6(1):10-16, (2010).

حول تحويل فوريير المحدود الموسعة لسلسلة زمنية مستمرة ثابتة مع وجود بيانات مفقودة

د. أميرة إبراهيم الدسوقي؛ أ. على محمد بن عروس؛ د. محمد أبو الفتوح غزال

المخلص: يبحث هذا البحث في خصائص تحويل فوريير المحدودة الموسعة لسلسلتين زمنيتين ذات قيمة متجهية ثابتة. يمكن تصور كلتا السلسلتين الزمنيتين على أنهما مستمرتان. هذه إحدى الخصائص التي تسمح لهم بالمرونة. يوفر تحويل فوريير المحدودة الموسعة الأساس لهذه الدراسة حيث أنه أثناء دراسة هذه الخصائص للسلسلتين الزمنيتين باستخدام تحويل فوريير الموسعة، يتم إجراء تحليل للبيانات، يتم خلال الدراسة استخدام أنماط السلاسل الزمنية الاعتيادية والغير اعتيادية ودراسة خصائصها أثناء إجراء التحليل.

الكلمات المفتاحية: تحويل فوريير المحدودة- البيانات المفقودة- السلاسل الزمنية المستمرة الثابتة- توزيع ويشارت- نوافذ البيانات