Using R, I fit a regression model that included an intercept, time, time^2, and three seasonal indicators. I then took the residuals and fit an ARIMA model.

I ended up fitting a SARIMA(3,3,1)x(3,0,2)_4 model to the residuals. I then forecasted the next four quarters.

<table>
<thead>
<tr>
<th>Predictions:</th>
<th>Here</th>
<th>From 3.39</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1</td>
<td>2.906</td>
<td>2.918</td>
</tr>
<tr>
<td>Q2</td>
<td>2.882</td>
<td>2.846</td>
</tr>
<tr>
<td>Q3</td>
<td>3.005</td>
<td>2.928</td>
</tr>
<tr>
<td>Q4</td>
<td>2.633</td>
<td>2.604</td>
</tr>
</tbody>
</table>

The two sets of forecasts are very similar.

Since the approach from 3.39 was easier to implement, I would choose that approach.

Please see my R code for full details.
Here's the plot. See my R code.

\[ \omega = \frac{6}{100} \quad A^2 = 13 \]

\[ \omega = \frac{10}{100} \quad A^2 = 41 \]

\[ \omega = \frac{40}{100} \quad A^2 = 85 \]

\text{sum}

The difference between this plot and the plot for \( n = 128 \) is that with \( n = 128 \), the

\[ \frac{6}{100}, \frac{10}{100}, \frac{40}{100} \]

are not

\text{fundamental frequencies. Thus the \# of cycles}

\text{completed by each component piece is not}

\text{exactly an integer when } n = 128. \]

(continued)
Here's the plot.

These other frequencies receive weight since
\[
\frac{6}{100}, \frac{10}{100} + \frac{40}{100} \text{ aren't fundamental.}
\]

Frequencies. They are fundamental frequencies when \( n = 100 \).
4.1 Here's the plot.

\[ \omega = \frac{6}{100} \quad A^2 = 13 \]

\[ \omega = \frac{10}{100} \quad A^2 = 41 \]

\[ \omega = \frac{40}{100} \quad A^2 = 85 \]

\[ \text{sum} \]

\[ \omega = \frac{10}{100} \quad A^2 = 41 \]

With the noise added, this plot is no longer perfectly periodic as it was in the textbook example.
The periodogram is noisier due to the added noise, but the 3 main frequencies are still very prominent.