Financial technology forecasting using an evolving connectionist system for lenders and borrowers: ecosystem behavior

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ABSTRACT
Financial technology (FinTech) which is included in the development of digitalization in the financial sector in the industrial era 4.0. FinTech can make any transactions anywhere with the pillars of peer-to-peer (P2P) lending, merchants, and crowdfunding. In the P2P lending pillar, there are borrowers and lenders who are digitized in FinTech devices. FinTech in Indonesia is controlled by a state agency called the financial services authority or otoritas jasa keuangan (OJK). In the movement of P2P lending, there are borrowers and lenders who can be said to be investors where these activities are reported to the OJK. This data can be forecasted using a neural network approach such as evolving connectionist system (ECoS), which is a method capable of forecasting with learning that develops in the hidden layer. In this research article, we present results on forecasting borrowers with a mean absolute percentage error (MAPE) of 0.148% and forecasting lenders with an accuracy measurement with MAPE of 0.209% with a learning rate 1=0.6 and a learning rate 2=0.3. So, this forecasting model can be said as an optimization in FinTech activities on the behavior of borrowers and lenders.

Keywords:
Evolving connectionist system
Financial technology
Forecasting
Peer-to-peer lending

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1. INTRODUCTION
Financial technology (FinTech) is an application in the financial sector that is able to carry out financial activities in any transaction and can be done anywhere [1]–[3]. There are various types of FinTech, ranging from merchant support to peer-to-peer (P2P) lending that matches loans and loan recipients [4]. FinTech, which is growing rapidly, is used because the process of making transactions is not like ordinary conventional transactions [5]. FinTech has also begun to conduct research, both in application development and in predicting the behavior of FinTech users [6]. FinTech is used in mobile payment so that transactions occur with openness and are able to increase profits for the industry [7]. While Bollaert et al. [8] describes the effect of FinTech developments in financial and investor behavior in business moves such as P2P lending, crowdfunding, and tenders.

In Indonesia, the activity process in FinTech is monitored by a state institution, namely the financial services authority or otoritas jasa keuangan (OJK) [9]. OJK oversees all activities in FinTech, where there are
registered FinTech and licensed Fintech. Licensed Fintech is FinTech with an ISO 270001 security system [10]. FinTech engaged in P2P lending is a FinTech activity that has borrowers and lenders of funds [11]. FinTech fund borrowers are users who are registered with FinTech by following the applicable requirements [12]. Meanwhile, FinTech lenders, who are often referred to as investors, are FinTech financiers who are digitized, conventional, or sharia [13]. However, in carrying out matching between lenders and loan recipients, a queuing model has been carried out as was done in [14] using a model to get smart customers and smart investors with a genetic algorithm approach.

From the available data, forecasting can be done in FinTech P2P lending activities in order to obtain data in the future [15]. Forecasting is also almost the same as predictions based on time series [16]. Forecasting is included in a technique that processes data into information that then becomes knowledge [17]–[19]. This forecasting uses supervised learning [20]. Various studies have been conducted to perform forecasting in business fields such as, Apichatibutarapong [21] perform forecasting on students who do business by utilizing mobile technology in addition to benefiting from statistical strategies in business. Besides that, Eveleens et al. [22] did forecasting to forecast decreases in industry assets every year so that it can assist in making decisions. Bandara et al. [23] performed forecasting on sales demand in e-commerce with the long short-term memory (LSTM) neural network approach by obtaining optimal results based on previous data. Whereas Yu and Li [24] did stock price index forecasting using the LSTM deep neural network approach, which obtained results based on the comparison values of 4 types of losses with the latest technology tools.

Various studies have been conducted on forecasting in business and the optimal method for forecasting in the financial sector is the evolving connectionist system (ECoS) [25]. ECoS is a super-fast learning from big data through one-pass based on new data which is accommodated in stages and is able to improve the process of searching for information and being able to learn data actively and interactively [26]. Various studies have been conducted in forecasting with ECoS in the business field as was done in [27] predicting gold prices using the evolving multilater perceptron which is the result of a development from the ECoS principle which yielded an accuracy value based on mean absolute percentage error (MAPE) of 0.769% based on learning rate 1 at 0.9 and learning rate 2 at 0.9. Whereas Al-Khowarizmi et al. [28] forecast crude palm oil (CPO) with the simple evolving connectionist system (SECoS) approach which is also a development of the ECoS principle where the results of this research are the latest research in the field of CPO and obtained high accuracy with a MAPE of 0.035% in forecasting with a learning rate of 1 at 0.9 and a learning rate of 2 at 0.6. This creates interest in forecasting loan providers and recipients in FinTech so that it becomes the basis for behavior in FinTech to find out the services provided to lenders and loan recipients.

2. MATERIAL AND METHOD

2.1. Dataset

In this paper we forecast the lenders and recipients of loans available on FinTech. FinTech in its business activities always reports to the institution that gives the permit. In this case, FinTech management in Indonesia is controlled by the OJK so that there is no money laundering in FinTech. The data used is based on [29] which can be accessed freely.

2.2. Forecasting with evolving connectionist system

ECoS in various studies is referred to as machine learning. Where the ECoS process is able to do various things with supervised learning. In forecasting with ECoS, several stages are carried out where the ECoS principle implemented in a neural network has 3 layers as shown in Figure 1.

In Figure 1 is a neural network by applying the ECoS principle. The neural network consists of 3 layers [30], [31]. The first layer is the input layer, the second layer is the hidden layer or it can be said as the evolving layer, and the third layer is the output layer [32]. Each neural network has a linear activation function that functions in the evolving node layer calculated in (1) and (2),

\[ A_n = 1 - D_n \]  
\[ D_n = \sqrt{\sum_k^{r} |I_k - W_k|^2} \]  

\[ A_n \] is the value of the activation function at node \( n \), \( D_n \) is the distance between the input vector \( I \), and the connection weight vector \( W \). The distance measure \( D_n \) is the normalized Euclidean. ECoS networks are used in the forecasting of FinTech as follows [33]–[35]:

a. Input vector \( I \) into the ECoS layer.

b. If the maximum activation value (Amax) from node \( I \) sensitivity threshold (Sth), then:

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- The node expands on the hidden layer
  If not:
  i) Calculate the error values between the output vectors $O_c$ and output vectors $O_d$.
  ii) If the error value $\geq$ the threshold error coefficient ($E_{\text{thr}}$) or the desired output node does not support it, then the node expands. If not, then update the connection weight on the winning hidden node.

### Figure 1. ECoS architecture

This step is required for every input vector without an epoch.

If the activation value does not meet the activation threshold, or the error exceeds the error threshold, a new neuron will be added. If a neuron is not added, the connection weights are updated. The process of updating connection weights in the hidden layer and output layer for node $j$ based on (3) and (4) [36].

\[
W_{i,j}(t+1) = W_{i,j}(t) + \eta_1 I_i - W_{i,j}(t) \\
W_{j,p}(t+1) = W_{j,p}(t) + \eta_2 A_j - E_p
\]

Where $W_{i,j}(t)$ is the weight value between input $i$, and hidden neuron $j$ at time $t$; $W_{i,j}(t+1)$ is the weight value between $i$ and $j$ at time $t+1$; $\eta_1$ is the learning rate 1 parameter; $I_i$ is the $i^{th}$ value in the input vector $I$; $W_{j,p}(t)$ is the weight value between $j$ and output $p$ at time $t$; $W_{j,p}(t+1)$ is the weight value between $j$ and $p$ at time $t+1$; $\eta_2$ is the learning rate 2 parameter; and $A_j$ is the activation value of the node $j$.

### 2.3. General architecture

In order for the research to be directed according to the desired results, a general architecture was designed in this paper. The general architecture in this paper is shown in Figure 2. This architecture follows these steps:

a. Crawling data on FinTech loan providers and recipients.
b. Determine the parameters of learning rate 1, learning rate 2, and dataset normalization with (5).

\[
\text{Normalized Data} = \frac{(x-x_{\text{min}})}{x_{\text{max}}-x_{\text{min}}}
\]
Where in generating normalized data $x$ the value to be normalized, $x_{\text{min}}$ the smallest value of the variable, and $x_{\text{max}}$ the largest value of the variable.

c. Calculation of the value of the activation function and distance with (1) and (2).

d. Conduct data training on the ECoS and update the weights. If the weights are not as specified, then return to the ECoS. If the weight is appropriate then proceed to step (e).

e. Perform data testing on the ECoS and update the weights. If the weight does not match the specified one, it returns to the ECoS. If the weight is appropriate then proceed to step (f).

f. Accuracy measurement with MAPE in (6).

$$ \text{MAPE} = \frac{\sum_{n=1}^{n} |a-b|}{a} \times 100\% \quad (6) $$

where in getting MAPE the value $a$ is the actual value, $b$ is the forecasting data, and $n$ is the total amount of data.

3. RESULTS AND DISCUSSION

In this paper, we forecast making and taking loans in FinTech, where the process is carried out using a super adaptive method, namely ECoS as outlined in SECoS. The research carried out is based on index data as outlined by the OJK in 2022. The data has been visualized based on the graph in Figure 3. From Figure 3 it can be seen that the data has been visualized from January 2022 to December 2022 borrower and lender data on FinTech P2P in Indonesia. From these data enter into data normalization where data is available before being processed with SECoS. The data after being normalized with a range of 0 to 1 can be seen in Table 1.

![General architecture](image)

After normalizing the data as in Table 1, the next step is to enter into the training and testing process. However, the SECoS algorithm is a machine learning algorithm that has been optimized with parameter selection. The parameters tested in this research are presented in Table 2.

From Table 2 it can be seen that the optimal parameters are learning rate $1=0.6$, learning rate $2=0.3$, sensitivity threshold $=0.3$, error threshold $=0.1$, and resulting 22 hidden nodes which expand with 36 trials. In conducting training and testing, of course, this cannot be separated from training data and data testing. The training data in this paper were carried out on January to August. The test data was September to December.
The data obtained has a high dimensionality where the data is from various regions in Indonesia which has been confirmed by the financial services authority. However, steps according to the general architecture are entered into data testing by entering back into the neural network so that the forecasting results for borrowers and lenders are clearly visible in Table 3. Table 3 is the result of forecasting based on step (e) on the general architecture. The results are clear that the SECoS algorithm is capable of forecasting borrowers and lenders on FinTech P2P data. The predicted values versus the original values are plotted in Figure 4.

![Figure 3. FinTech financial dataset](image-url)

Table 1. Dataset normalization

<table>
<thead>
<tr>
<th>Date</th>
<th>Borrower</th>
<th>Lender</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jan-22</td>
<td>0</td>
<td>0.00212225</td>
</tr>
<tr>
<td>Feb-22</td>
<td>0.29365303</td>
<td>0</td>
</tr>
<tr>
<td>Mar-22</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Apr-22</td>
<td>0.4433957</td>
<td>0.57932187</td>
</tr>
<tr>
<td>May-22</td>
<td>0.52016468</td>
<td>0.62017201</td>
</tr>
<tr>
<td>Jun-22</td>
<td>0.74067153</td>
<td>0.79896803</td>
</tr>
<tr>
<td>Jul-22</td>
<td>0.5596764</td>
<td>0.65776491</td>
</tr>
<tr>
<td>Aug-22</td>
<td>0.58405191</td>
<td>0.68677301</td>
</tr>
<tr>
<td>Sep-22</td>
<td>0.61334979</td>
<td>0.71518282</td>
</tr>
<tr>
<td>Oct-22</td>
<td>0.53069083</td>
<td>0.65127857</td>
</tr>
<tr>
<td>Nov-22</td>
<td>0.55687819</td>
<td>0.69217653</td>
</tr>
<tr>
<td>Dec-22</td>
<td>0.61739175</td>
<td>0.73594983</td>
</tr>
</tbody>
</table>

Table 2. Optimal process in setting parameters

<table>
<thead>
<tr>
<th>No</th>
<th>Sensitivity threshold</th>
<th>Error threshold</th>
<th>Learning rate 1</th>
<th>Learning rate 2</th>
<th>Hidden node</th>
</tr>
</thead>
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<tr>
<td>1</td>
<td>0.9</td>
<td>0.1</td>
<td>0.3</td>
<td>0.3</td>
<td>29</td>
</tr>
<tr>
<td>2</td>
<td>0.9</td>
<td>0.1</td>
<td>0.3</td>
<td>0.6</td>
<td>38</td>
</tr>
<tr>
<td>3</td>
<td>0.9</td>
<td>0.1</td>
<td>0.3</td>
<td>0.9</td>
<td>36</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>20</td>
<td>0.3</td>
<td>0.1</td>
<td>0.3</td>
<td>0.6</td>
<td>34</td>
</tr>
<tr>
<td>21</td>
<td>0.3</td>
<td>0.1</td>
<td>0.3</td>
<td>0.9</td>
<td>34</td>
</tr>
<tr>
<td>22</td>
<td>0.3</td>
<td>0.1</td>
<td>0.6</td>
<td>0.3</td>
<td>22</td>
</tr>
<tr>
<td>23</td>
<td>0.3</td>
<td>0.1</td>
<td>0.6</td>
<td>0.6</td>
<td>34</td>
</tr>
<tr>
<td>24</td>
<td>0.3</td>
<td>0.1</td>
<td>0.6</td>
<td>0.9</td>
<td>35</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>34</td>
<td>0.3</td>
<td>0.05</td>
<td>0.9</td>
<td>0.3</td>
<td>29</td>
</tr>
<tr>
<td>35</td>
<td>0.3</td>
<td>0.05</td>
<td>0.9</td>
<td>0.9</td>
<td>38</td>
</tr>
<tr>
<td>36</td>
<td>0.3</td>
<td>0.05</td>
<td>0.9</td>
<td>0.9</td>
<td>38</td>
</tr>
</tbody>
</table>
Table 3. Borrower and lender forecasting results

<table>
<thead>
<tr>
<th>Date</th>
<th>Forecast borrower</th>
<th>Forecast lender</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sep-22</td>
<td>0.70197206</td>
<td>0.90321764</td>
</tr>
<tr>
<td>Oct-22</td>
<td>0.69358005</td>
<td>0.89012112</td>
</tr>
<tr>
<td>Nov-22</td>
<td>0.63392072</td>
<td>0.79293649</td>
</tr>
<tr>
<td>Dec-22</td>
<td>0.61539344</td>
<td>0.78353783</td>
</tr>
</tbody>
</table>

Figure 4. Borrower forecasting results

From the picture, the 4 blue dots are the original values from FinTech and the orange ones are the forecast values. If you pay close attention to the December point of the original value and the forecasting value, the point is so close to the value between 0.61739175 and 0.61539344, this shows that the error value achieved is small. The forecast lender data is plotted in Figure 5.

Figure 5. Lender forecasting results

Figure 5 shows that the blue dot is the original value from FinTech and the orange color is the forecasting value from the lender. If you pay close attention to the December point of the original value and...
forecasting value, then the point is so close to the value between 0.73759493 and 0.78353783, this shows that the error value achieved is small. After achieving the forecasting value, of course, a validation test is needed with the MAPE accuracy technique. Based on (6), the borrower's MAPE value is shown.

$$\text{MAPE(Borrower)} = \frac{\sum [0.59301090]}{4} \times 100\% = 0.148\%$$

Meanwhile, the MAPE from the lender is:

$$\text{MAPE (Lender)} = \frac{\sum [0.8375044]}{4} \times 100\% = 0.209\%$$

A satisfactory calculation process can of course be seen in the process of forecasting with the SECoS algorithm on FinTech data in ecosystem behavior between lenders and loan recipients where FinTech can be accessed anywhere, so the forecasting process is very much needed by the FinTech industry.

4. CONCLUSION

It is generally a concern that FinTech P2P is receiving attention from various countries. This been unified on FinTech P2P data in Indonesia. These results make it clear that SECoS can provide optimization in machine learning algorithms on data training and testing. The optimization results from the process of training and testing SECoS by developing its own structure such as the hidden layer and output layer. This research has been tested with the parameter learning rate $l=0.6$, learning rate $2=0.3$, sensitivity threshold=0.3, error threshold=0.1 with hidden node=22. The satisfactory results show that in forecasting borrowers achieve MAPE of 0.148% and in forecasting lenders MAPE of 0.209%.

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REFERENCES


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