While GRNN possesses some strength in functional mapping, its intrinsic mathematical operations render it weaker than most econometric models in predicting values in the state space which extends beyond the training data. On the other hand, most econometric models are capable of extrapolating values outside of the existing/known data range during forecasting process. Given this notion, we propose a two-stage model which combines an econometric model with GRNN to overcome this shortcoming and to create synergies in the overall forecasting process. In this two-stage model, an econometric model is used to generate a forecast in the 0rst stage. In the second stage, a GRNN is applied to correct the estimation error in the 0rst stage forecast. It is hoped that this error correction by the neural network can lead to an improvement in the 0nal forecast. The fundamental concept of the proposed hybrid approach originates from adaptive forecasting

which attempts to uncover possible data patterns not captured by a forecasting model in the 0rst pass. During the second pass in the forecasting process, another forecasting model is applied to pick up potential data patterns hidden in the residual term. A vast majority of the models utilized in this adaptive forecasting paradigm have a rather traditional econometric background. Most of these econometric models are linear in their functional forms and hold under speci0c parametric assumptions. Our proposed hybrid approach deviates from this tradition as it combines the strengths of a neural network and a multivariate econometric model. Furthermore, the approach takes an unconventional step of applying a nonparametric (neural network) model to learn and thus reduce the errors made by various parametric (econometric) models. This approach can also be roughly viewed as nonweighted forecast combination in a sequential manner. In the current study, adaptive error correction models are used to forecast one-quarter-ahead exchange rates. Their forecasting performances are then compared with several competing models including the ones solely based on single forecasting techniques. Our investigation of GRNN has been motivated by the neural network’s attractive properties discussed earlier. In the next section, we will provide the economic rationale associated with currency exchange rate forecasting. In Section 3, we present a brief review and mathematical foundation of GRNN and those econometric techniques used in this research. Then, the data set and our estimation procedures are explained in Section 4. Statistical performances of the two-stage error correction models are reported in Section 5. This section also includes comparisons with the single-stage econometric and GRNN models (i.e., models used to directly forecast the exchange rates). In Section 6, we describe a simulation experiment designed to measure the pro0t derived from the trading of various currencies. A background of the trading decision rules and a discussion of the trading experiment results are also given. The paper is then concluded in Section 7.

2. Literature review 2.1. Economic background There are several theories of exchange rate determination normally used in empirical studies:

the Kexible price monetary model, the sticky price monetary model, the Hooper–Morton model, the portfolio balance model, and the uncovered interest parity model. The Kexible price monetary model, the sticky price monetary model, and the Hooper–Morton model are essentially di6erent versions of the monetary approach. Of these three monetary approaches, the Hooper–Morton model is the more general model and encompasses the other two models. Meese and Rogo6 [12], Alexander and Thomas [13], Schinasi and Swamy [14], and Meese and Rose [15] are examples of studies which use the monetary approach and the Hooper–Morton model. Sarantis and Stewart [16] provide a good review and description of the main theoretical exchange rate models. Moreover, the study reports a detailed econometric evaluation of all of the theoretical models mentioned above for sterling exchange rates using the cointegration-error correction methodology. Later Sarantis and Stewart [5] show that the exchange rate forecasting models based on the uncovered interest parity (UIP) relationship produce more accurate out-of-sample forecasts. In addition, the empirical study shows that the Bayesian vector autoregression (BVAR) model based on UIP produces the best short-term forecasts, which also outperform the random walk forecasts. Following the 0ndings from these previous studies, we adopt the UIP relationship as the theoretical

basis for our exchange rate forecasting models. The UIP relationship can be cast in the following general forecasting form: