



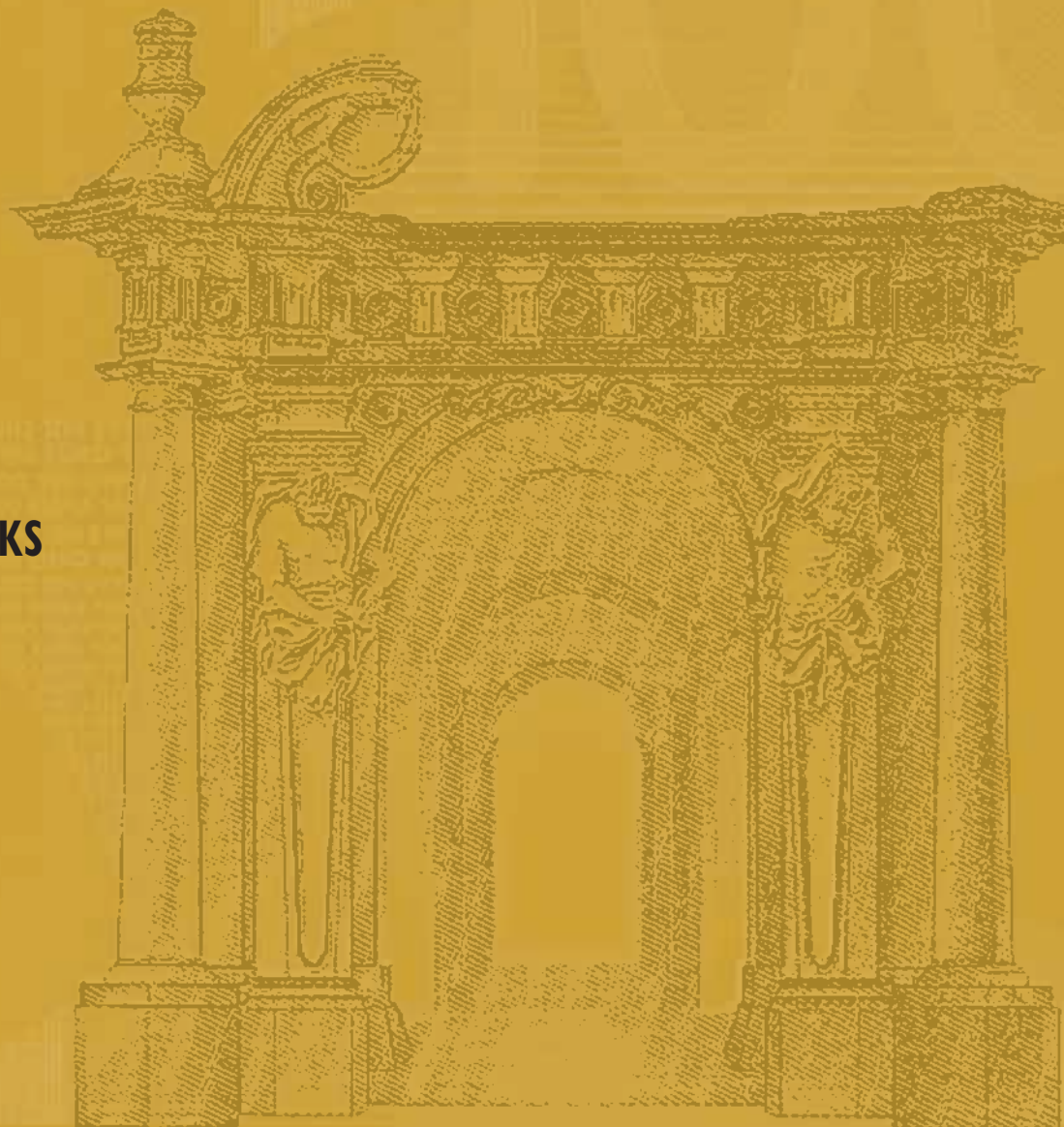
EUROPEAN CENTRAL BANK

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**FORECASTING
INFLATION
WITH THICK
MODELS AND
NEURAL NETWORKS**

by Paul McNelis
and Peter McAdam





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Abstract: This paper applies linear and neural network-based “thick” models for forecasting inflation based on Phillips–curve formulations in the USA, Japan and the euro area. Thick models represent “trimmed mean” forecasts from several neural network models. They outperform the best performing linear models for “real-time” and “bootstrap” forecasts for service indices for the euro area, and do well, sometimes better, for the more general consumer and producer price indices across a variety of countries.

JEL: C12, E31.

Keywords: Neural Networks, Thick Models, Phillips curves, real-time forecasting, bootstrap.

Non-Technical Summary

This paper applies linear and neural network-based “thick” models (NN) for forecasting inflation based on Phillips–curve formulations in the USA, Japan and the euro area. Thick models represent “trimmed mean” forecasts from several neural network models. This “thick model” based on the NN specification is benchmarked against a well-performing linear process. The appeal of the NN is that it efficiently approximates a wide class of non-linear relations.

Our results show that non-linear Phillips curve specifications based on thick NN models can be competitive with the linear specification. We have attempted a high degree of robustness in our results by using different countries, different indices and sub-indices as well as performing different types of out-of-sample forecasts using a variety of supporting metrics. The “thick” NN models show the best “real-time” and bootstrap forecasting performance for the service-price indices for the Euro area. The performance of the neural network relative to a recursively-updated well-specified linear model should not be taken for granted. Given that the linear coefficients are changing each period, there is no reason not to expect good performance, especially in periods when there is little or no structural change taking place. We show in this paper that the linear and neural network specifications converge in their forecasts in such periods. The payoff of the neural network “thick modeling” strategy comes in periods of structural change and uncertainty, such as the early 1990’s in the USA and Germany, and after 2000 in the USA. When we examine the components of the CPI, we note that the non-linear models prove more accurate especially for forecasting inflation in the services sector. Since the service sector is, by definition, a highly labor-intensive industry and closely related to labor-market developments, this result appears to be consistent with recent research on relative labor-market rigidities and asymmetric adjustment.

1. Introduction

Forecasting is a key activity for policy makers. Given the possible complexity of the processes underlying policy targets, such as inflation, output gaps, or employment, and the difficulty of forecasting in real-time, recourse is often taken to simple models. A dominant feature of such models is their linearity. However, recent evidence suggests that simple, though non-linear, models may be at least as competitive as linear ones for forecasting macro variables. Marcellino (2002), for example, reported that non-linear models outperform linear and time-varying parameter models for forecasting inflation, industrial production and unemployment in the euro area. Indeed, after evaluating the performance of the Phillips curve for forecasting US inflation, Stock and Watson (1999) acknowledged that “to the extent that the relation between inflation and some of the candidate variables is non-linear”, their results may “understate the forecasting improvements that might be obtained, relative to the conventional linear Phillips curve” (p327). Moreover, Chen *et al.* (2001) examined linear and (highly non-linear) Neural Network Phillips-curve approaches for forecasting US inflation, and found that the latter models outperformed linear models for ten years of “real-time” one-period rolling forecasts.

Our paper contributes to this important debate in a number of respects. We follow Stock and Watson and concentrate on Phillips curves for forecasting inflation. However, we do so using linear and encompassing non-linear approaches. We further use a transparent comparison methodology. To avoid “model-mining”, our approach first identifies the best performing linear model and then compares that against a trimmed-mean forecast of simple non-linear models, which Granger and Jeon (2004) call a “thick model”. We examine the robustness of our inflation forecasting results by using different countries (and country aggregates), with different indices and sub-indices as well as conducting several types of out-of-sample comparisons using a variety of metrics.

Specifically, using the Phillips-curve framework, this paper applies linear and “thick” neural networks (NN) to forecast monthly inflation rates in the USA, Japan and the euro area. For the latter, we examine relatively long time series for Germany, France, Italy and Spain (comprising over 80% of the aggregate) as well as for the euro-area aggregate. The appeal of the NN is that it efficiently approximates a wide class of non-linear relations. Our goal is to see how well this approach performs relative to the standard linear one, for forecasting with “real-time” and randomly-generated “split sample” or “bootstrap” methods. In the “real-time” approach, the coefficients are updated period-by-period in a rolling window, to generate a sequence of one-period-ahead predictions. Since policy makers are usually interested in predicting inflation at twelve-month horizons, we estimate competing models for this horizon, with the bootstrap and real-time forecasting approaches. It turns out that the “thick model” based on trimmed-mean forecasts of several NN models dominates in many cases the linear model for the out-of-sample forecasting with the bootstrap and the “real-time” method.

Our “thick model” approach to neural network forecasting follows on recent reviews of neural network forecasting methods by Zhang *et al.*, (1998). They acknowledge that the proper specification of the structure of a neural network is a “complicated one” and note that there is no theoretical basis for selecting one specification or another for a neural network [Zhang *et al.*, (1998) p. 44]. We acknowledge this model uncertainty and consequently make use of the “thick model”

as a sensible way to utilize alternative neural network specifications and “training methods” in a “learning” context.

The paper proceeds as follows. The next section lays out the basic model. Section 3 discusses key properties of the data and the methodological background. Section 4 presents the empirical results for the US, Japan, the euro area, and Germany, France, Italy and Spain for the in-sample analysis, as well as for the twelve-month split-sample forecasts and examines the “real-time” forecasting properties for the same set of countries. Section 5 concludes.

2. The Phillips Curve

We begin with the following forecasting model for inflation:

$$\pi_{t+h}^h - \pi_t = f(\Delta u_t, \dots, \Delta u_{t-k}, \Delta \pi_t, \dots, \Delta \pi_{t-m}) + e_{t+h} \quad (1)$$

$$\pi_{t+h}^h = \frac{1200}{h} \ln \left(\frac{P_t}{P_{t-h}} \right) \quad (2)$$

where π_{t+h} is the percentage rate of inflation for the price level P , at an annualized value, at horizon $t+h$, u is the unemployment rate, e_{t+h} is a random disturbance term, while k and m represent lag lengths for unemployment and inflation. We estimate the model for $h=12$. Given the discussion on the appropriate measure of inflation for monetary policy (e.g., Mankiw and Reis, 2003) we forecast using both the Consumer Price Index (CPI) and the producer price index (PPI) as well as indices for food, energy and services.

The data employed are monthly and seasonally adjusted. US data comes from the Federal Reserve of St. Louis FRED data base, while the Euro Area is from the European Central Bank.¹ The data for the remaining countries come from the OECD Main Economic Indicators.

3. Non-linear Inflation Processes

Should the inflation/unemployment relation or inflation/economic activity relation be linear? Figures 1 and 2 picture the inflation unemployment relation in the euro area and the USA, respectively and Table I lists summary statistics.

¹ Euro-area data, notably, has been widely used – inter alia, Galí *et al.* (2001), Smets and Wouters (2003), McAdam and Willman (2004).

Figure 1— Euro-Area Phillips curves: 1988-2001

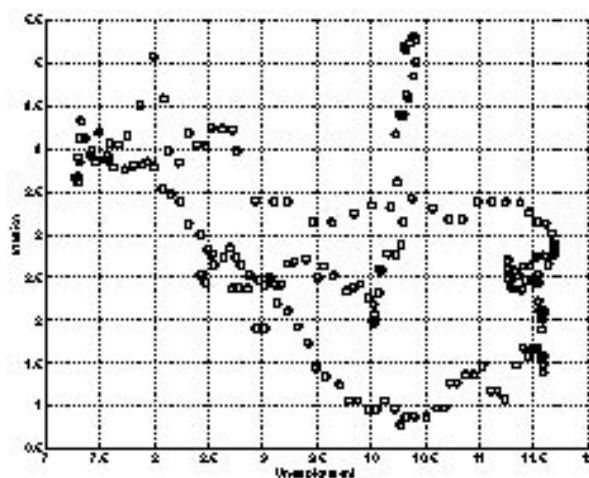


Figure 2— USA Phillips curves: 1988-2001

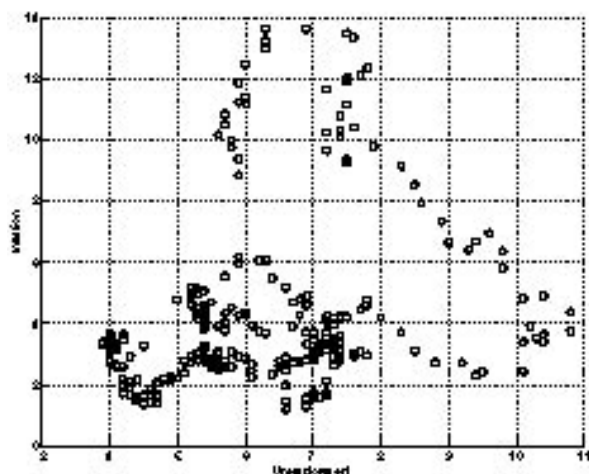


Table I—Summary Statistics

	Euro area		USA	
	<i>Inflation</i>	<i>Unemployment</i>	<i>Inflation</i>	<i>Unemployment</i>
Mean	2.84	9.83	3.16	5.76
Std. Dev.	1.07	1.39	1.07	1.07
Coeff. Var.	0.37	0.14	0.34	0.18

As we see, the average unemployment rate is more than four percentage points higher in the Euro Area than in the USA, and, as shown by the coefficient of variation, is less volatile. U.S. inflation, however, is only slightly higher than in the euro area, and its volatility is not appreciably different.

Need less to say, such differences in national economic performance have attracted considerable interest. In one influential analysis, for instance, Ljungqvist and Sargent (2001) point out that not only the average level but also the duration of euro-

area unemployment have exceeded the rest of the OECD during the past two decades – a feature they attribute to differences in unemployment compensation. Though, during the less turbulent 1950's and 1960's, European unemployment was lower than that of the US, with high lay-off costs, through a high tax on “job destruction”, they note that this lower unemployment may have been purchased at an “efficiency cost” by “making workers stay in jobs that had gone sour” (p. 19). When turbulence increased, and job destruction finally began to take place, older workers could be expected to choose extended periods of unemployment, after spending so many years in jobs in which both skills and adaptability significantly depreciated. This suggests that a labor market characterized by high layoff costs and generous unemployment benefits will exhibit asymmetries and “threshold behavior” in its adjustment process. Following periods of low turbulence, unemployment may be expected to remain low, even as shocks begin to increase. However, once a critical threshold is crossed, when the costs of staying employed far exceed layoff costs, unemployment will graduate to a higher level; those older workers whose skills markedly depreciated may be expected to seek long-term unemployment benefits.

The Ljungqvist and Sargent explanation of European unemployment is by no means exhaustive. Such unemployment dynamics may reflect a complex interaction among many factors, e.g., Lindbeck (1997), Blanchard and Wolfers (2000). However, notwithstanding the different emphasis of such many explanations, the general implication is that we might expect a non-linear estimation process with threshold effects, such as NNs, to outperform linear methods, for detecting underlying relations between unemployment and inflation in the euro area. At the very least, we expect (and in fact find) that non-linear approximation works better than linear models for inflation indices most closely related to changes in the labor market in the euro area – inflation in the price index for services.

3.1 *Neural Networks Specifications*

In this paper, we make use of a hybrid alternative formulation of the NN methodology: the basic multi-layer perceptron or feed-forward network, coupled with a linear jump connection or a linear neuron activation function. Following McAdam and Hughes-Hallett (1999), an encompassing NN can be written as:

$$n_{k,t} = \omega_0 + \sum_{i=1}^I \omega_i x_{t,i} + \sum_{j=1}^J \phi_j N_{t-1,j} \quad (3)$$

$$N_{k,t} = h(n_{k,t}) \quad (4)$$

$$y_{i,t} = \gamma_{i,0} + \sum_{k=1}^K \gamma_{i,k} N_{k,t} + \sum_{i=1}^I \beta_i x_{i,t} \quad (5)$$

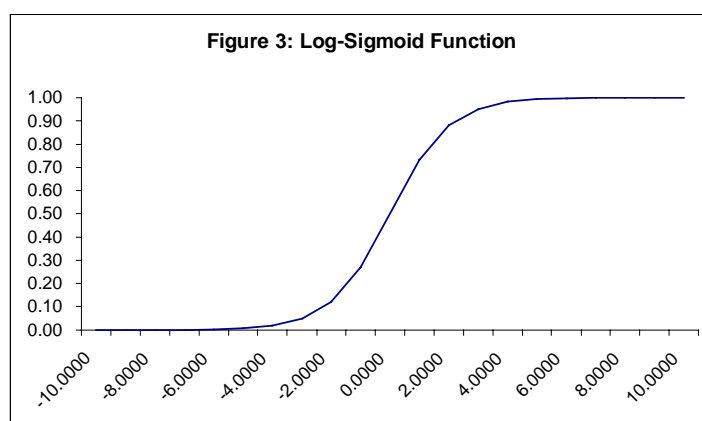
where inputs (x) represent the current and lagged values of inflation and unemployment, and the outputs (y) are their forecasts and where the I regressors are combined linearly to form K neurons, which are transformed or “encoded” by the

“squashing” function. The K neurons, in turn, are combined linearly to produce the “output” forecast.²

Within this system, (3)–(5), we can identify representative forms. **Simple** (or standard) **Feed-Forward**, $\phi_j = \beta_i = 0, \forall i, j$, namely links inputs (x) to outputs (y) via the hidden layer. Processing is thus *parallel* (as well as sequential); in equation (5) we have both a linear combination of the inputs and a limited-domain mapping of these through a “squashing” function, h , in equation (4). Common choices for h include the log-sigmoid form, $N_{k,t} = h(n_{k,t}) = \frac{1}{1 + e^{-n_{k,t}}}$ (Figure 3) which transforms data to

within a unit interval: $h: R \rightarrow [0,1]$, $\left\{ \begin{array}{l} \lim_{n \rightarrow \infty} h(n) \rightarrow 1 \\ \lim_{n \rightarrow -\infty} h(n) \rightarrow 0 \end{array} \right.$. Other, more sophisticated,

choices of the squashing function are considered in section 3.3.



The attractive feature of such functions is that they represent threshold behavior of the type previously discussed. For instance, they model representative non-linearities (e.g. a Keynesian liquidity trap where “low” interest rates fail to stimulate the economy or “labor-hoarding” where economic downturns have a less than proportional effect on layoffs etc). Further, they exemplify agent learning – at extremes of non-linearity, movements of economic variables (e.g., interest rates, asset prices) will generate a less than proportionate response to other variables. However if this movement continues, agents learn about their environment and start reacting more proportionately to such changes.

We might also have **Jump Connections**, $\phi_j \neq 0, \forall j, \beta_i = 0, \forall i$: direct links from the inputs, x , to the outputs. An appealing advantage of such a network is that it nests the pure linear model as well as the feed-forward NN. If the underlying relationship between the inputs and the output is a pure linear one, then only the direct jump connectors, given by $\{ \beta_i \}$, $i = 1, \dots, I$, should be significant. However, if the true

² Stock (1999) points out that the LSTAR (logistic smooth transition autoregressive) method is a special case of NN estimation. In this case, $y_{t+h} = \alpha(L)y_t + d_t \beta(L)y_t + u_{t+h}$, the switching variable d_t is a log-sigmoid function of past data, and determines the “threshold” at which the series switches.

relationship is a complex non-linear one, then one would expect $\{\omega\}$ and $\{\gamma\}$ to be highly significant, while the coefficient set $\{\beta\}$ to be relatively insignificant. Finally, if the underlying relationship between the inputs variables $\{x\}$ and the output variable $\{y\}$ can be decomposed into linear and non-linear components, then we would expect all three sets of coefficients, $\{\beta, \omega, \gamma\}$ to be significant. A practical use of the jump connection network is that it is a useful test for neglected non-linearity in a relationship between the input variables x and the output variable y .³

In this study, we examine this network with varying specifications for the number of neurons in the hidden layers, jump connections. The lag lengths for inflation and unemployment changes are selected on the basis of in-sample information criteria.

3.2 *Neural Network Estimation and Thick Models*

The parameter vectors of the network, $\{\omega\}, \{\gamma\}, \{\beta\}$ may be estimated with non-linear least squares. However, given its possible convergence to local minima or saddle points (e.g., see the discussion in Stock, 1999), we follow the hybrid approach of Quagliarella and Vicini (1998): we use the genetic algorithm for a reasonably large number of generations, one hundred, then use the final weight vector $[\{\hat{\omega}\}, \{\hat{\gamma}\}, \{\hat{\beta}\}]$ as the initialization vector for the gradient-descent minimization based on the quasi-Newton method. In particular, we use the algorithm advocated by Sims (2003).

The genetic algorithm proceeds in the following steps: (1) create an initial population of coefficient vectors as candidate solutions for the model; (2) have a selection process in which two different candidates are selected by a fitness criterion (minimum sum of squared errors) from the initial population; (3) have a cross-over of the two selected candidates from step (3) in which they create two offspring; (4) mutate the offspring; (5) have a "tournament", in which the parents and offspring compete to pass to the next generation, on the basis of the fitness criterion. This process is repeated until the population of the next generation is equal to the population of the first. The process stops after "convergence" takes place with the passing of one hundred generations or more. A description of this algorithm appears in the appendix.⁴

Quagliarella and Vicini (1998) point out that hybridization may lead to better solutions than those obtainable using the two methods individually. They argue that it is not necessary to carry out the gradient descent optimization until convergence, if one is going to repeat the process several times. The utility of the gradient-descent algorithm is its ability to improve the individuals it treats, so its beneficial effects can be obtained just performing a few iterations each time.

Notably, following Granger and Jeon (2004), we make use of a "thick modeling" strategy: combining forecasts of several NNs, based on different numbers of neurons in the hidden layer, and different network architectures (feedforward and jump connections) to compete against that of the linear model. The combination forecast is the "trimmed mean" forecast at each period, coming from an ensemble of networks, usually the same network estimated several times with different starting values for the parameter sets in the genetic algorithm, or slightly different networks.

³ For completeness, a final case in this encompassing framework is Recurrent networks, (Elman, 1988), $\phi_j = 0 \forall j, \beta_i \neq 0 \forall i$, with current and lagged values of the inputs into system (memory). Although, this less popular network, is not used in this exercise. For an overview of NNs, see White (1992).

⁴ See Duffy and McNelis (2001) for an example of the genetic algorithm with real, as opposed to binary, encoding.



We numerically rank the predictions of the forecasting model then remove the 100* α % largest and smallest cases, leaving the remaining 100*(2- α)% to be averaged. In our case, we set α at 5%. Such an approach is similar to forecast combinations. The trimmed mean, however, is fundamentally more practical since it bypasses the complication of finding the optimal combination (weights) of the various forecasts.

3.3 Adjustment and Scaling of Data

For estimation, the inflation and unemployment “inputs” are stationary transformations of the underlying series. As in equation (1), the relevant forecast variables are the one-period-ahead first differences of inflation.⁵

Besides stationary transformation, and seasonal adjustment, scaling is also important for non-linear NN estimation. When input variables $\{x_t\}$ and stationary output variables $\{y_t\}$ are used in a NN, “scaling” facilitates the non-linear estimation process. The reason why scaling is helpful is that the use of very high or small numbers, or series with a few very high or very low outliers, can cause underflow or overflow problems, with the computer stopping, or even worse, or as Judd (1998, p.99) points out, the computer continuing by assigning a value of zero to the values being minimized.

There are two main ranges used in linear scaling functions: as before, in the unit interval, $[0, 1]$, and $[-1, 1]$. Linear scaling functions make use of the maximum and minimum values of series. The linear scaling function for the $[0, 1]$ case transforms a variable x_k into x_k^* in the following way:⁶

$$x_{k,t}^* = \frac{x_{k,t} - \min(x_k)}{\max(x_k) - \min(x_k)} \quad (6)$$

A non-linear scaling method proposed by Helge Petersohn (University of Leipzig), transforming a variable x_k to z_k allows one to specify the range $0 < z_k < 1$, or $(0,1)$, given by $[\max(z_k), \min(z_k)] = [\bar{z}_k, \underline{z}_k]$:

$$z_{k,t} = \left(1 + \exp \left[\left(\frac{\ln(\bar{z}_k^{-1} - 1) - \ln(\underline{z}_k^{-1} - 1)}{\max(x_k) - \min(x_k)} \right) [x_{k,t} - \min(x_k)] + \ln(\underline{z}_k^{-1} - 1) \right] \right)^{-1} \quad (7)$$

Finally, Dayhoff and De Leo (2001) suggest scaling the data in a two step procedure: first, standardizing the series x , to obtain z , then taking the log-sigmoid transformation of z :

$$z = \frac{x - \bar{x}}{\sigma_x} \quad (8)$$

⁵ As in Stock and Watson (1999), we find that there are little noticeable differences in results using seasonally adjusted or unadjusted data. Consequently, we report results for the seasonally adjusted data.

⁶ The linear scaling function for $[-1,1]$, transforming x_k into x_k^{**} , has the form, $x_{k,t}^{**} = 2 \frac{x_{k,t} - \min(x_k)}{\max(x_k) - \min(x_k)} - 1$.

$$x^* = \frac{1}{1 + \exp(-z)} \quad (9)$$

Since there is no a priori way to decide which scaling function works best, the choice depends critically on the data. The best strategy is to estimate the model with different types of scaling functions to find out which one gives the best performance. When we repeatedly estimate various networks for the “ensemble” or trimmed mean forecast, we use identical networks employing different scaling function.

In our “thick model” approach, we use all three scaling functions for transforming the input variables. For the hidden layer neurons, we use the logsigmoid functions for the neural network forecasts. The networks are simple, with one, two or three neurons in one hidden-layer, with randomly-generated starting values⁷, using the feedforward and jump connection network types. We thus make use of twenty different neural network “architectures” in our thick model approach. These are twenty different randomly-generated integer values for the number of neurons in the hidden layer, combined with different randomly generated indicators for the network types and indicators for the scaling functions. Obviously, our thick model approach can be extended to a wider variety of specifications but we show, even with this smaller set, the power of this approach.⁸

In nonlinear neural network estimation, there is no closed-form solution for obtaining the parameter values of the network. The final values of the parameter estimates, and thus the predicted values of inflation, even with convergence, may be slightly different, depending on the choice of the scaling function and the starting values of the estimates, for a given neural network structure. Since we are also varying the network structure, of course, we will have a spectrum of predicted values. From this set we derived the trimmed mean forecast. This “thick model” approach is similar to “bagging predictors” in the machine learning and artificial intelligence literature (see Breiman, 1996).

3.4 *The Benchmark Model and Evaluation Criteria*

We examine the performance of the NN method relative to the benchmark linear model. In order to have a fair “race” between the linear and NN approaches, we first estimate the linear auto-regressive model, with varying lag structures for both inflation and unemployment. The optimal lag length for each variable, for each data set, is chosen based on the Hannan-Quinn criterion. We then evaluate the in-sample diagnostics of the best linear model to show that it is relatively free of specification error. For most of the data sets, we found that the best lag length for inflation, with the monthly data, was ten or eleven months, while one lag was needed for unemployment.

After selecting the best linear model and examining its in-sample properties, we then apply NN estimation and forecasting with the “thick model” approach discussed above, for the same lag length of the variables, with alternative NN

⁷ We use different starting values as well as different scaling functions in order to increase the likelihood of finding the global, rather than a local, minimum.

⁸ We use the same lag structure for both the neural network and linear models. Admittedly, we do this as simplifying computational short cut. Our goal is thus to find the “value added” of the neural network specification, given the benchmark best linear specification. This does not mean that alternative lag structures may work even better for neural network forecasting, relative to the benchmark best linear specification of the lag structure.

structures of two, three, or four neurons, with different scaling functions, and with feedforward, jump connection and We estimate this network alternative for thirty different iterations, and take the “trimmed mean” forecasts of this “thick model” or network ensemble, and compare the forecasting properties with those of the linear model.

3.4.1 *In-sample diagnostics*

We apply the following in-sample criteria to the linear auto-regressive and NN approaches:

- R^2 goodness-of-fit measure - denoted R^2 ;
- Ljung-Box (1978) and McLeod-Li (1983) tests for autocorrelation and heteroskedasticity - **LB** and **ML**, respectively;
- Engle-Ng (1993) LM test for symmetry of residuals - **EN**;
- Jarque-Bera test for Normality of regression residuals - **JB**;
- Lee-White-Granger (1992) test for neglected non-linearity - **LWG**;
- Brock-Dechert-Scheinkman (1987) test for independence, based on the “correlation dimension” - **BDS**;

3.4.2 *Out-of-sample forecasting performance*

The following statistics examine the out-of-sample performance of the competing models:

- The root mean squared error estimate - **RMSQ**;
- The Diebold-Mariano (1995) test of forecasting performance of competing models - **DM**;
- The Persaran-Timmerman (1992) test of directional accuracy of the signs of the out-of-sample forecasts, as well as the corresponding success ratios, for the signs of forecasts - **SR**;
- The bootstrap test for “in-sample” bias.

For the first three criteria, we estimate the models recursively and obtain “real-time” forecasts. For the US data, we estimate the model from 1970.01 through 1990.01 and continuously update the sample, one month at a time, until 2003.01. For the euro-area data, we begin at 1980.01 and start the recursive real-time forecasts at 1995.01.

The bootstrap method is different. This is based on the original bootstrapping due to Efron (1983), but serves another purpose: out-of-sample forecast evaluation. The reason for doing out-of-sample tests, of course, is to see how well a model

generalizes beyond the original training or estimation set or historical sample, for a reasonable number of observations. As mentioned, the recursive methodology allows only one out-of-sample error for each training set. The point of any out-of-sample test is to estimate the “in-sample bias” of the estimates, with a sufficiently ample set of data. LeBaron (1997) proposes a variant of the original bootstrap test, the “0.632 bootstrap” (described in Table II).⁹ The procedure is to estimate the original in-sample bias by repeatedly drawing new samples from the original sample, with replacement, and using the new samples as estimation sets, with the remaining data from the original sample, not appearing in the new estimation sets, as clean test or out-of-sample data sets. However, the bootstrap test does not have a well-defined distribution, so there are no “confidence intervals” that we can use to assess if one method of estimation dominates another in terms of this test of “bias”.

Table II—“0.632” Bootstrap Test for In-Sample Bias

Obtain mean square error from estimation set	$SSE(n) = \frac{1}{n} \sum_{i=1}^n [y_i - \hat{y}_i]^2$
Draw B samples of length n from estimation set	z_1, z_2, \dots, z_B
Estimate coefficients of model for each set	$\Omega^1, \Omega^2, \dots, \Omega^B$
Obtain “out of sample” matrix for each sample	$\tilde{z}_1, \tilde{z}_2, \dots, \tilde{z}_B$
Calculate average mean square error for “out of sample”	$SSE(n_b) = \frac{1}{n_b} \sum_{i=1}^{n_b} [\tilde{z}_b - \hat{z}_b(\Omega^b)]^2$
Calculate average mean square error for B bootstraps	$SSE(B) = \frac{1}{B} \sum_{b=1}^B SSE(n_b)$
Calculate “bias adjustment”	$\tilde{\omega}^{(0.632)} = 0.632[SSE(n) - SSE(B)]$
Calculate “adjusted error estimate”	$SSE^{(0.632)} = (1 - 0.632)SSE(n) + 0.632SSE(B)$

4 Results¹⁰

Table III contains the empirical results for the broad inflation indices for the USA, the euro area (as well as Germany, France, Spain and Italy) and Japan. The data set for the USA begins in 1970 while the European and Japanese series start in 1980. We “break” the USA sample to start “real-time forecasts” at 1990.01 while the other countries break at 1995.01.

⁹ LeBaron (1997) notes that the weighting 0.632 comes from the probability that a given point is actually in a given bootstrap draw, $1 - \left[1 - \frac{1}{n}\right]^n \approx 0.632$.

¹⁰ The (Matlab) code and the data set used in this paper is available on request.

Table III—Diagnostic / Forecasting Results

	USA CPI	PPI	Euro Area CPI	PPI	Germany CPI	PPI	France CPI	PPI	Spain CPI	PPI	Italy CPI	PPI	Japan CPI	WPI
LAGS-Inf	10	10	11	11	10	10	10	10	11	10	10	10	11	11
LAGS-Un	1	1	1	1	1	1	1	1	1	1	1	1	1	1
RSQ-LS	0.992	0.992	0.998	0.997	0.993	0.993	0.993	0.994	0.995	0.994	0.994	0.995	0.996	0.992
L-B *	0.948	0.851	0.414	0.094	0.956	0.892	0.992	0.910	0.937	0.799	0.828	0.667	0.885	0.985
McL-L *	0.829	0.000	0.003	0.867	0.880	0.835	0.592	0.318	0.452	0.818	0.258	0.491	0.976	0.854
E-N *	0.628	0.000	0.019	0.640	0.984	0.832	0.758	0.031	0.516	0.713	0.669	0.216	0.273	0.769
J-B *	0.001	0.000	0.016	0.005	0.234	0.000	0.020	0.000	0.000	0.000	0.989	0.000	0.284	0.000
LWG	0	1	7	1	0	0	0	0	1	1	1	1	2	1
BDS *	0.083	0.000	0.117	0.360	0.819	0.637	0.215	0.416	0.128	0.091	0.531	0.346	0.993	0.528
RSQ-NET	0.992	0.992	0.998	0.997	0.994	0.993	0.993	0.994	0.995	0.994	0.994	0.995	0.996	0.992
RMSQ-LS	0.214	0.386	0.167	0.358	0.308	0.303	0.225	0.368	0.178	0.368	0.207	0.305	0.340	0.340
RMSQ-NET	0.213	0.385	0.167	0.343	0.307	0.302	0.224	0.371	0.180	0.371	0.206	0.304	0.339	0.333
SR-LS	0.986	0.971	0.973	0.973	0.978	0.940	0.963	0.989	1.000	0.989	0.988	0.989	0.986	0.943
SR-NET	0.986	0.971	0.973	0.973	0.978	0.940	0.976	0.989	1.000	0.989	0.988	0.989	0.986	0.943
DM-1 *	0.036	0.088	0.568	0.000	0.092	0.218	0.344	0.768	0.600	0.768	0.267	0.067	0.117	0.014
DM-2 *	0.043	0.104	0.565	0.002	0.073	0.221	0.335	0.807	0.591	0.807	0.235	0.091	0.098	0.048
DM-3 *	0.029	0.087	0.571	0.002	0.108	0.230	0.358	0.796	0.599	0.796	0.228	0.099	0.074	0.060
DM-4 *	0.033	0.118	0.571	0.000	0.086	0.261	0.356	0.773	0.601	0.773	0.042	0.099	0.076	0.087
DM-5 *	0.019	0.108	0.584	0.000	0.076	0.243	0.345	0.778	0.611	0.778	0.220	0.096	0.080	0.100
Bootstrap SSE-LS	0.079	0.182	0.031	0.116	0.078	0.101	0.043	0.068	0.117	0.091	0.041	0.106	0.136	0.100
Bootstrap SSE-NET	0.079	0.181	0.030	0.116	0.078	0.101	0.043	0.068	0.117	0.091	0.039	0.106	0.136	0.100
Ratio	0.997	0.993	0.990	0.996	1.000	0.999	0.998	0.999	1.003	0.993	0.954	1.002	1.000	1.002

*: represents probability values

Note: Bold indicates those series which show superior performance of the network, either in terms of Diebold-Mariano or bootstrap ratios.

DM_1, ... DM_5 etc allow for the out of sample forecast errors to be corrected for autocorrelations at lags one through 5.

What is clear across a variety of countries is that the lag lengths for both inflation and unemployment are practically identical. With such a lag length, not surprisingly, the overall in-sample explanatory power of all of the linear models is quite high, over 0.99. The marginal significance levels of the Ljung-Box indicate that we cannot reject serial independence in the residuals.¹¹ The McLeod-Li tests for autocorrelation in the squared residuals are insignificant except for the US producer price index and the aggregate euro-area CPI. For most countries, we can reject normality in the regression residuals of the linear model (except for Germany, Italian and Japanese CPI). Furthermore, the Lee-White-Granger and Brock-Decker-Scheinkman tests do not indicate “neglected non-linearity”, suggesting that the linear auto-regressive model, with lag length appropriately chosen, is not subject to obvious specification error. This model, then, is a “fit” competitor for the neural network “thick model” for out-of-sample forecasting performance.

The forecasting statistics based on the root mean squared error and success ratios are quite close for the linear and network thick model. What matters, of course, is the significance: are the real-time forecast errors statistically “smaller” for the network model, in comparison with the linear model? The answer is not always. At the ten percent level, the forecast errors, for given autocorrelation corrections with the Diebold-Mariano statistics, are significantly better with the neural network approach for the US CPI and PPI, the euro area PPI, the German CPI, the Italian PPI and the Japanese CPI and WPI.

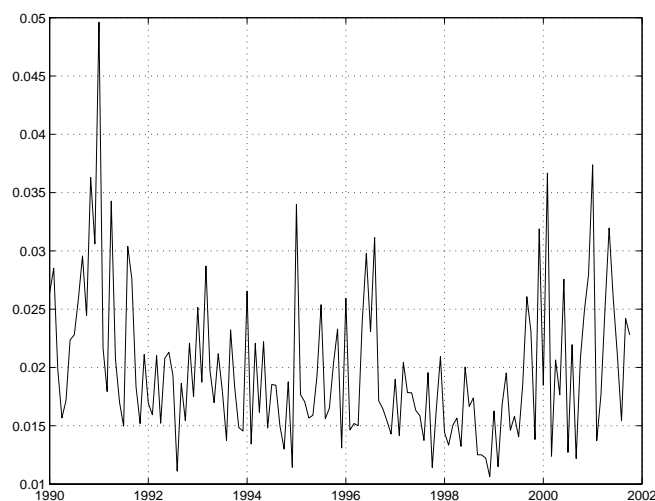
To be sure, the reduction in the root mean squared error statistic from moving to network methods is not dramatic, but the “forecasting improvement” is significant for the USA, Germany, Italy, and Japan. The bootstrapping sum of squared errors shows a small gain (in terms of percentage improvement) from moving to network

¹¹ Since our dependent variable is a 12-month-ahead forecast of inflation, the model by construction has a moving average error process of order 12, one current disturbance and 11 lagged disturbances. We approximate the MA representation with an AR (12) process, which effectively removes the serial dependence.

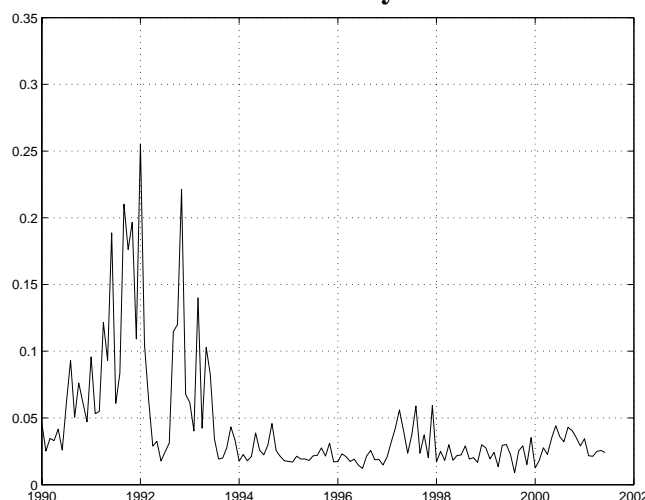
methods for the USA CPI and PPI, the euro area CPI and PPI, France CPI and PPI, Spain PPI and Italian CPI and PPI. For Italy, the percentage improvement in the forecasting is greatest for the CPI, with a gain or percentage reduction of almost five percent. For the other countries, the network error-reduction gain is less than one percent.

The usefulness of this “think modeling” strategy for forecasting is evident from an examination of Figures 4 and 5. In these figures, we plot the standard deviations of the set of forecasts for each out-of-sample period of all of the models. This comprises at each period twenty-two different forecasts, one linear, one based on the trimmed mean, and the remaining twenty neural network forecasts.

**Figure 4: Thick Model Forecast Uncertainty:
USA**



**Figure 5: Thick Model Forecast Uncertainty:
Germany**



We see in these two figures that the thick model forecast uncertainty is highest in the early 1990's in the USA and Germany, and after 2000 in the USA. In Germany,

this highlights the period of German unification. In the USA, the earlier period of uncertainty is likely due to the first Gulf War oil price shocks. The uncertainty after 2000 in the USA is likely due to the collapse of the US share market.

What is most interesting about these two figures is that models diverge in their forecasts in times of abrupt structural change. It is, of course, in these times that the thick model approach is especially useful. When there is little or no structural change, models converge to similar forecasts, and one approach does about as equally well as any other.

What about sub-indices? In Table IV, we examine the performance of the two estimation and forecasting approaches for food, energy and service components for the CPI for the USA and euro area.

Table IV—Food, Energy and Services Indices, Diagnostics and Forecasting

	USA			Euro Area		
	Food	Energy	Services	Food	Energy	Services
LAGS-INFLATION	10	11	10	10	10	10
LAGS-UNEMPLOY	1	6	1	1	1	1
RSQ-LS	0.992	0.993	0.993	0.994	0.993	0.996
L-B *	0.728	0.971	0.465	0.565	0.217	0.696
McL-L *	0.000	0.043	0.001	0.498	0.583	0.619
E-N *	0.000	0.075	0.000	0.442	0.374	0.883
J-B *	0.000	0.000	0.000	0.386	0.005	0.742
LWG	5	0	15	1	1	0
BDS *	0.000	0.000	0.000	0.092	0.938	0.342
RSQ-NET	0.991	0.994	0.993	0.996	0.993	0.997
RMSQ-LS	0.322	2.123	0.129	0.333	0.770	0.246
RMSQ-NET	0.32	2.144	0.129	0.334	0.775	0.230
SR-LS	0.949	0.974	0.961	0.961	0.941	0.941
SR-NET	0.955	0.974	0.955	0.961	0.941	0.941
DM-1 *	0.511	0.882	0.354	0.900	0.846	0.000
DM-2 *	0.512	0.854	0.313	0.876	0.801	0.000
DM-3 *	0.513	0.848	0.339	0.891	0.800	0.000
DM-4 *	0.513	0.839	0.324	0.934	0.793	0.001
DM-5 *	0.514	0.812	0.348	0.936	0.829	0.002
Bootstrap SSE-LS	0.402	3.001	0.049	0.067	0.428	0.086
Bootstrap SSE-NET	0.41	2.992	0.048	0.067	0.426	0.080
Ratio	0.998	0.994	0.981	0.997	0.995	0.934

*: represents probability values

Note: See notes to Table III

The lag structures are about the same for these models as the overall CPI indices, except for the USA energy index, which has a lag length of unemployment of six. The results only show a market “real-time forecasting” improvement for the service component of the euro area. However the bootstrap method shows a reduction in the forecasting error “bias” for all of the indices, with the greatest reductions in forecasting error, of almost seven percent, for the services component of the euro area.

5 Conclusions

Forecasting inflation other industrialized countries is a challenging task. Notwithstanding the costs of developing tractable forecasting models, accurate forecasting is a key component of successful monetary policy. All our chosen countries have undergone major structural and economic-policy regime changes over the past two to three decades, some more dramatically than others. Any model, however complex, cannot capture all of the major structural characteristics affecting the underlying inflationary process. Economic forecasting is a learning process, in which we search for better subsets of approximating models for the true underlying process. Here, we examined one set of approximating alternative, a “thick model” based on the NN specification, benchmarked against a well-performing linear process. We do not suggest that the network approximation is the only alternative or the best among a variety of alternatives¹². However, the appeal of the NN is that it efficiently approximates a wide class of non-linear relations.

Our results show that non-linear Phillips curve specifications based on thick NN models can be competitive with the linear specification. We have attempted a high degree of robustness in our results by using different countries, different indices and sub-indices as well as performing different types of out-of-sample forecasts using a variety of supporting metrics. The “thick” NN models show the best “real-time” and bootstrap forecasting performance for the service-price indices for the Euro area, consistent with, for instance, the analysis of Ljungqvist and Sargent (2001). However, these approaches also do well, sometimes better, for the more general consumer and producer price indices for the US, Japan and European countries.

The performance of the neural network relative to a recursively-updated well-specified linear model should not be taken for granted. Given that the linear coefficients are changing each period, there is no reason not to expect good performance, especially in periods when there is little or no structural change taking place. We show in this paper that the linear and neural network specifications converge in their forecasts in such periods. The payoff of the neural network “thick modeling” strategy comes in periods of structural change and uncertainty, such as the early 1990’s in the USA and Germany, and after 2000 in the USA.

When we examine the components of the CPI, we note that the nonlinear models work especially for forecasting inflation in the services sector. Since the service sector is, by definition, a highly labor-intensive industry and closely related to labor-market developments, this result appears to be consistent with recent research on relative labor-market rigidities and asymmetric adjustment.

¹² One interesting competing approximating model is the auto-regressive model with drifting coefficients and stochastic volatilities, e.g., Cogley and Sargent (2002).

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Appendix:

Evolutionary Stochastic Search: The Genetic Algorithm

Both the Newton-based optimization (including back propagation) and Simulated Annealing (SA) start with a random initialization vector Ω_0 . It should be clear that the usefulness of both of these approaches to optimization crucially depend on how “good” this initial parameter guess really is. The genetic algorithm (GA) helps us come up with a better “guess” for using either of these search processes. In addition, the GA avoids the problems of landing in a local minimum, or having to approximate the Hessians. Like Simulated Annealing, it is a statistical search process, but it goes beyond SA, since it is an *evolutionary search process*. The GA proceeds in the following steps.

Population creation

This method starts not with one random coefficient vector Ω , but with a population N^* (an even number) of random vectors. Letting p be the size of each vector, representing the total number of coefficients to be estimated in the NN, one creates a population N^* of p by 1 random vectors:

$$\begin{pmatrix} \Omega_1 \\ \Omega_2 \\ \vdots \\ \Omega_p \end{pmatrix}_1 \begin{pmatrix} \Omega_1 \\ \Omega_2 \\ \vdots \\ \Omega_p \end{pmatrix}_2 \begin{pmatrix} \Omega_1 \\ \Omega_2 \\ \vdots \\ \Omega_p \end{pmatrix}_i \dots \begin{pmatrix} \Omega_1 \\ \Omega_2 \\ \vdots \\ \Omega_p \end{pmatrix}_{N^*} \quad (11)$$

Selection

The next step is to select two pairs of coefficients from the population at random, with replacement. Evaluate the “fitness” of these four coefficient vectors according to the sum of squared error function given above. Coefficient vectors which come closer to minimizing the sum of squared errors receive “better” fitness values.

One conducts a simple fitness “tournament” between the two pairs of vectors: the winner of each tournament is the vector with the best “fitness”. These two winning vectors (i, j) are retained for “breeding” purposes:

$$\begin{pmatrix} \Omega_1 \\ \Omega_2 \\ \vdots \\ \Omega_p \end{pmatrix}_i \begin{pmatrix} \Omega_1 \\ \Omega_2 \\ \vdots \\ \Omega_p \end{pmatrix}_j \quad (12)$$

Crossover

The next step is crossover, in which the two parents “breed” two children. The algorithm allows “crossover” to be performed on each pair of coefficient vectors i and j , with a fixed probability $p > 0$. If crossover is to be performed, the algorithm uses one of three difference crossover operations, with each method having an equal (1/3) probability of being chosen:

- *Shuffle crossover.* For each pair of vectors, k random draws are made from a binomial distribution. If the k^{th} draw is equal to 1, the coefficients $\Omega_{i,p}$ and $\Omega_{j,p}$ are swapped; otherwise, no change is made.
- *Arithmetic crossover.* For each pair of vectors, a random number is chosen, $\omega \in (0,1)$. This number is used to create two new parameter vectors that are linear combinations of the two parent factors, $\omega\Omega_{i,p} + (1-\omega)\Omega_{j,p}$, $(1-\omega)\Omega_{i,p} + \omega\Omega_{j,p}$.
- *Single-point crossover.* For each pair of vectors, an integer I is randomly chosen from the set $[1, k-1]$. The two vectors are then cut at integer I and the coefficients to the right of this cut point, $\Omega_{i,I+1}$, $\Omega_{j,I+1}$ are swapped.

In binary-encoded genetic algorithms, single-point crossover is the standard method. There is no consensus in the genetic algorithm literature on which method is best for real-valued encoding.

Following the operation of the crossover operation, each pair of “parent” vectors is associated with two “children” coefficient vectors, which are denoted C1(i) and C2(j). If crossover has been applied to the pair of parents, the children vectors will generally differ from the parent vectors.

Mutation

The fifth step is mutation of the children. With some small probability $\tilde{p}\tilde{r}$, which decreases over time, each element or coefficient of the two children's vectors is subjected to a mutation. The probability of each element is subject to mutation in generation $G = 1, 2, \dots, G^*$, given by the probability $\tilde{p}\tilde{r} = 0.15 + 0.33/G$.

If mutation is to be performed on a vector element, one uses the following non-uniform mutation operation, due to Michalewicz (1996). Begin by randomly drawing two real numbers r_1 and r_2 from the $[0,1]$ interval and one random number s ,

from a standard normal distribution. The mutated coefficient $\tilde{\Omega}_{i,p}$ is given by the following formula:

$$\tilde{\Omega}_{i,p} = \begin{cases} \Omega_{i,p} + s \left[1 - r_2^{1-G/G^*} \right] & \text{if } r_1 > 0.5 \\ \Omega_{i,p} - s \left[1 - r_2^{1-G/G^*} \right] & \text{if } r_1 \leq 0.5 \end{cases} \quad (13)$$

where G is the generation number, G^* is the maximum number of generations, and b is a parameter which governs the degree to which the mutation operation is non-uniform. Usually one sets $b = 2$ and $G^* = 150$. Note that the probability of creating a new coefficient via mutation, which is far from the current coefficient value, diminishes as $G \rightarrow G^*$. This mutation operation is non-uniform since, over time, the algorithm is sampling increasingly more intensively in a neighborhood of the existing coefficient values. This more localized search allows for some fine-tuning of the coefficient vector in the later stages of the search, when the vectors should be approaching close to a global optimum.

Election tournament

The last step is the election tournament. Following the mutation operation, the four members of the “family” (P1, P2, C1, C2) engage in a fitness tournament. The children are evaluated by the same fitness criterion used to evaluate the parents. The two vectors with the best fitness, whether parents or children, survive and pass to the next generation, while the two with the worst fitness value are extinguished.

One repeats the above process, with parents i and j returning to the population pool for possible selection again, until the next generation is populated by N^* vectors.

Elitism

Once the next generation is populated, introduce elitism. Evaluate all the members of the new generation and the past generation according to the fitness criterion. If the “best” member of the older generation dominated the best member of the new generation, then this member displaces the worst member of the new generation and is thus eligible for selection in the coming generation.

Convergence

One continues this process for G^* generations, usually $G^*=150$. One evaluates convergence by the fitness value of the best member of each generation.

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