A Comparative Evaluation of the Estimation of Effort-Profit Relationships in the Scottish Demersal Trawl Fishery

B J Revell[1] and S. Pascoe[2]
1. Harper Adams University College, Newport, Shropshire, UK
2. CEMARE, University of Portsmouth, UK

Abstract. Generalised linear estimation and multi-layer perception neural network modelling techniques were applied to the Scottish trawler fleet data in order to estimate which inputs have the greatest impact on boat profits and output. Both produced comparable estimates that revealed inelastic and non-linear response to vessel power and length, negative response to vessel size (tonnage), and elastic response to both trip frequency and trip duration. Profit and catch-effort elasticities were greater for smaller vessels.

1. INTRODUCTION

A key assumption applied in fisheries economics is that the primary economic motivation of the skipper is to generate profit from the application of inputs. The physical process of transforming his inputs to outputs is through the production function, a concept that links fisheries technology into the economic model of fishing through the effort-harvest function. However, the vessel incurs costs in acquiring its outputs, and generates revenues from these outputs. For the individual firm (vessel), we may assume that the prices of its output or catch are exogenous, given that any individual vessel is unlikely to affect the market prices it receives.

The relationship between inputs and outputs has generally been examined through the estimation of production functions (e.g. Bjorndal 1989, Campbell, 1991) or stochastic production frontiers (e.g. Kirkley, Squires and Strand 1998; Sharma and Leung, 1999; Squires and Kirkley 1999, Eggert 2001, Pascoe *et al* 2001, Pascoe and Coglan, 2002). A criticism of these approaches has been the reliance on a single production function. While flexibility can be introduced into the production function through adopting a flexible functional form (e.g. translog), the function still implicitly assumes a common production technology.

Neural networks have been proposed as an alternative method for estimating the relationship between inputs and outputs. These avoid any functional form assumptions, and are driven purely by the observed input-output combinations.

In this paper, the potential usefulness of neural networks for assessing profit elasticities is examined. The results are compared with a traditional generalised linear modelling approach.

2. METHODOLOGIES AND MODEL SPECIFICATIONS

Two methodologies were used to estimate profit-effort response functions for the Scottish demersal trawler fleet: Multi-layer perceptron (MLP) neural network modelling; and Generalised Linear Modelling.[1] The two approaches are contrasting in that one utilises optimal search procedures to determine parameters, and the other classical statistical estimation and inference[2].

2.1 Neural Network Models

Neural network modelling involves search procedures to determine a set of optimal weights minimising a prediction error function, in which input/independent variables can interact through a hidden layer of nodes which themselves then contribute to the final output/ dependent variable. Inputs are scaled and converted into outputs through the hidden layer nodes and a logistic transfer function with threshold levels. The neural network is capable of modelling many non-linear response functions and surfaces. Hence it may also usefully even serve

[1] See McCullagh and Nelder (1989) for details on Generalized linear models
[2] Estimation of neural networks and GLZ estimators was through Statistica V 5.5, Statsoft Corportation

as a diagnostic tool in determining the functional form of multivariate relationships which may be subsequently estimated using classical regression approaches. Furthermore, the modelling process will iteratively search for an optimal input variable set and number of hidden layers .

Neural network models generate response functions to individual input variables through the network weights and logistic transfer function. Elasticity estimates have thus to be obtained through simulating change in the input variable of interest and measuring proportionate change in the output variable, for given levels of the other input variables (normally held at their mean values).

2.2 GLZ Modelling and Choice of Functional Forms

Generalised linear modelling (GLZ) not only permits multiple dependent variables and co-linearity of the independent variables, but more significantly, it enables the modelling of dependent variable which are non-normally distributed, permits non-linearity in the function linking the dependent and independent variables, and permits either factorial or other interactions between independent variables. Initial analyses of the data (see next section) found that profit and total weight of catch for the fleet were approximately gamma distributed, rather than normally distributed. Consequently, GLZ is more appropriate than OLS.

A response surface can be generally written as

$$y = \alpha + \sum_{i=1}^{n} \beta_i \cdot x_i + \frac{1}{2} \cdot \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} \cdot x_i \cdot x_j \tag{1}$$

where _$_{ij}$ = _$_{ji}$. The translog function is a variant of this, given by

$$\ln(y) = \alpha + \sum_{i=1}^{n} \beta_i \cdot \ln(x_i) + \frac{1}{2} \cdot \sum_{i=1}^{n} \sum_{j=1}^{n} \omega_{ij} \cdot \ln(x_i) \cdot \ln(x_j) \tag{2}$$

in which all variables are in natural logarithms. The surface function (1) would normally be estimated as

$$y = \left[\alpha + \left[\sum_{i=1}^{n} \beta_i \cdot x_i + \gamma_i \cdot (x_i)^2 \right] + \left(\sum_{i=1}^{n} \sum_{j=i+1}^{n} \omega_k \cdot x_i \cdot x_j \right) \right] \tag{3}$$

where _$_k$ is sequentially numbered **k = 1,2,… n(n-1)*2^{-1}** .

Based on preliminary analyses, it was found that the most appropriate general functional form for the fleet data used was an exponential link function, given by

$$y = \exp\left[\alpha + \left[\sum_{i=1}^{n} \beta_i \cdot x_i + \gamma_i \cdot (x_i)^2 \right] + \left(\sum_{i=1}^{n} \sum_{j=i+1}^{n} \omega_k \cdot x_i \cdot x_j \right) \right] \tag{4}$$

If there are no interaction terms through the independent variables (_$_k$ = 0 for all k), the model collapses to a quadratic function.

The elasticity of the function (4) wrt $\mathbf{x_i}$ is given by

$$\varepsilon_i = \left[\beta_i \cdot x_i + 2 \cdot \gamma_i \cdot (x_i)^2 \right] + \sum_{j=i+1}^{n} \omega_j \cdot x_i \cdot x_j \tag{5}$$

3. DATA CHARACTERISTICS

3.1 Revenue and input data

Information on the level of outputs and inputs of the Scottish demersal trawl fleet were available from the Scottish Office Agriculture and Fisheries Department (SOAFD)[3] individual vessel logbook data for 1997. Within this, vessels recorded as Bottom Otter Trawlers represented the major part of the activity. Data recorded included gear type, vessel characteristics, days at sea, weight of declared/landed catch, species of catch (although aggregated into round fish, flat fish, monkfish, nephrops and other species), and total value of catch. These data were recorded for each vessel and for each fishing trip. For the bottom otter trawl fleet, these data represented almost 10,400 observations/cases. Vessel identification was altered to preserve anonymity and confidentiality, although individual vessels could still be identified.

The key variable means for the individual trip data set are summarised in Table 1. The fleet has also been subdivided into power size groups in order to examine at the estimation phase whether vessel power size group affects effort response coefficients (different slopes) and, given the non-constant elasticities, which derive from the proposed functional form, how elasticity varies by power size group. The table shows that Group 2 dominates the sample with almost 50% of trips with the fleet averaging almost 6 days absence per trip

Table 1 Summary of Means for Bottom Otter Trawl 1997 per Trip Dataset

	Power groups					
	PG1	PG2	PG3	PG4	PG5	All Groups
kWh	< 200	200 <400	400 <600	600 <800	>800	
Length	14.2	19.9	24.4	26.5	29.5	20.8
GRT	22.8	48.1	109.2	170.3	267.7	73.6
Power (kWh)	140.0	318.4	488.1	685.3	904.8	373.3
Days Absent	2.4	5.5	7.6	8.8	9.3	5.9
Catch (tonnes)	1.3	5.2	10.8	13.1	11.7	6.7
Catch Value £	1045	5664	11107	14912	15031	7273
Profit (£)	1008	5115	9651	12460	11505	6361
No. obs	1811	4826	2411	1231	51	10330

The same data analysed per vessel over the 1997 season are presented in Table 2. The dataset has been cleaned and a number of extreme observations filtered out to facilitate statistical estimation and analysis[4]. This subset represents some 251 vessels. The key characteristics of this subset do not differ significantly from the individual trip dataset averages. The table also shows that on average, the fleet made between 27 and 28 trips per annum, and that the smaller vessels make more trips of shorter duration, and spend less total time at sea than the larger vessels.

Table 2 Vessel Characteristics: Annual sub-sample

	Power groups					
	PG1	PG2	PG3	PG4	PG5	All Groups
Length	15.4	19.8	24.2	27.1	36.1	21.1
GRT	26.9	48.4	93.5	161.8	423.9	72.5
Power (kWh)	140.7	313.6	472.7	682.2	1251.5	376.0
No. Trips	36.6	28.5	22.6	22.9	18.8	27.6
Mean Days Absent	2.8	5.6	7.8	8.4	8.9	6.0
Total Days Absent	92.1	154.8	173.4	194.0	169.0	154.2
Mean Catch (tonnes)	37	151	232	313	308	171
Total Profit (£)	40507	140492	198746	224209	225280	149004
no. obs	35	132	55	25	4	251

[3] Now Scottish Executive Rural Environment and Agriculture Department (SERAD)
[4] Excludes vessels which had a gross annual profit in excess of £0.5 million and vessels making less than 10 trips per annum, on the assumption that they are not full-time fishing vessels.

Although characteristics such as vessel length, tonnage and power (excluding auxiliary power units) may be considered as fixed inputs for an individual vessel, for the fleet as a whole, we may view these are variable,. In essence we thus estimate a hybrid function in which the scale of technology is not strictly constant. Nevertheless, given that vessel characteristics can be regulated in the longer run, it is of interest to policymakers to understand how these characteristics affect output[5].

3.2 Costs

The profit estimates in Tables 1 and 2 were derived from subtracting trip costs from the derived revenue figures. Clearly, the absence of cross-sectional questionnaire–based survey data created a difficulty in defining vessel costs, which form a key component of the economic motivation, profit. However, survey data from an earlier project[6] enabled indicative vessel cost functions to be estimated based on the vessel characteristics of gross tonnage, vessel power and length.

A cost function of total daily vessel fuel and lubricant costs was then estimated, with registered tonnage and vessel power as independent variables. Other direct costs data such as provisions, ice etc were not available for all vessels in the survey. Crew costs are normally based on a share of (quasi) profit, and hence may be considered a fixed cost.

The cost function estimates as a quadratic in vessel power and linear in tonnage are given in Table 3. All variables were significant and the fit was relatively good.

Table 3 Vessel Daily Cost Function Parameter Estimates

	Coeff	St. error	t(23)	p-level
Intercept	-62.14	31.70	-1.96	0.062194
GRT	0.56	0.16	3.45	0.002163
Power	0.46	0.097	5.3	2.15E-05
Power^2	-0.00015	3.59E-05	-4.16296	0.000375
Adjusted R_= .903				
F(3,23)=81.237 p<.00000 Std.Error of estimate: 40.425				

Vessel costs per trip for the Scottish Office survey data were then generated from the estimated daily cost function multiplied by the number of days each trip.

4. NEURAL NETWORK MODEL ESTIMATES AND RESULTS: FISHING EFFORT

The models were estimate both at the trip level and at the annual aggregated level. The latter reduces the size of the data set to the number of vessels in the fleet, and also reduces some of the noise in what is inherently noisy data.

4.1 Individual Vessel -Trip Model

The optimal model for the individual vessel-trip dataset of 10336 observations was a MLP 3:3:1 with 3 inputs (length, power and days absent), 3 hidden layers and a single output (profit). A diagrammatic representation of the network is presented in Figure 1, and the corresponding network weight estimates are presented in Table 4. The trip data are inherently very noisy, given the wide range of vessels and variation in catch from trip to trip. The model performance, as measured by the root mean square prediction error was 0.63, which approximates to a coefficient of determination of 0.4.

The profit response to the effort variables are shown in Figures 2. All are non-linear. Response to vessel power and length is montonically increasing within the data range found in the fleet, suggesting that restrictions on vessel length and power can reduce effort and catch.

---

[5] Indeed nested functions for vessels grouped according to power were estimated in order to test whether harvest-effort relationships did vary according to power. The estimates however were non significant and hence the more general estimates for all vessels in the fleet were preferred.

[6] Contract No. 94/26 "Economic Efficiency of the CFP and Social Objectives in Coastal Areas: A Comparative Study in Greece and Scotland", Final Report April 1997

Table 4 Network Weight Estimates MLP3:3:1 Vessel Profit Effort Trip Model

Input :	h1:1	h1:2	h1:3	Threshold
Threshold	0.70	-1.24	-2.11	
Length	0.98	1.75	-0.32	
Power	0.46	1.18	-0.37	
Days Absent	0.89	-2.13	-4.68	
h : Output	-1.77	1.70	-1.45	-0.57

n= 10,338

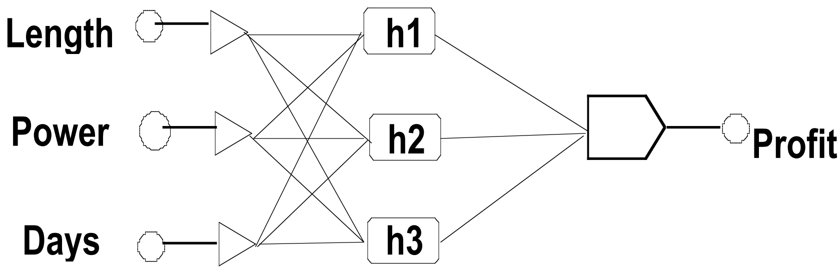

Fig 1 Network Illustration for Individual Trip Data

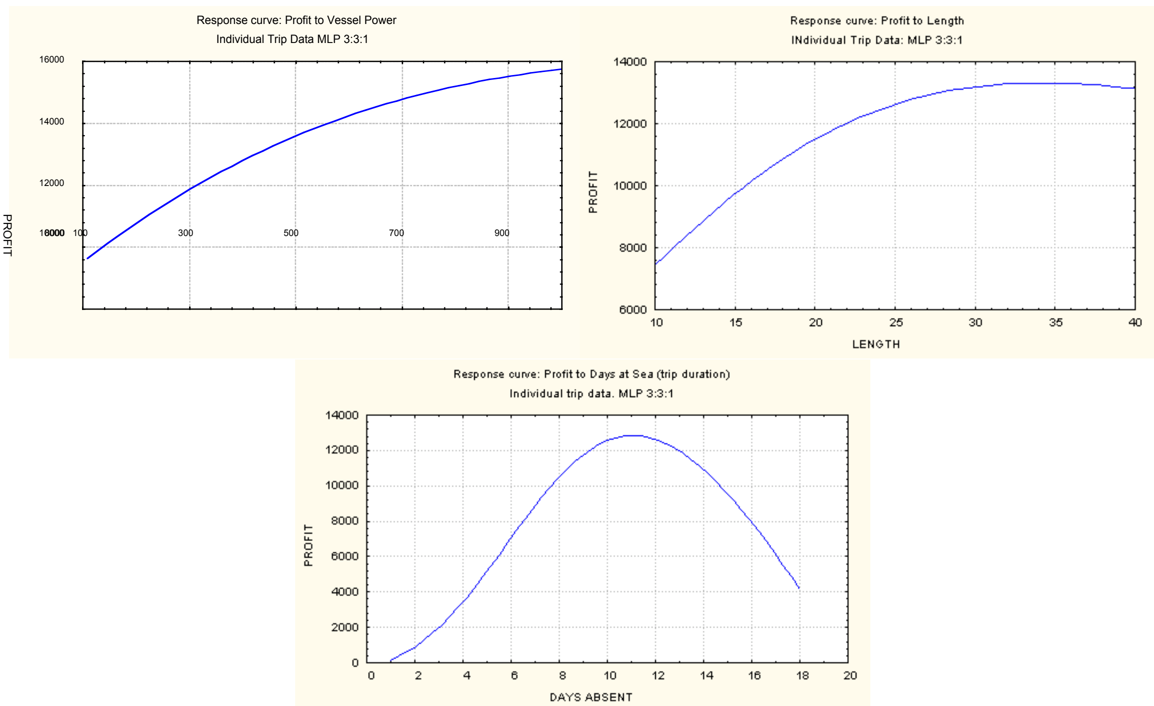

Fig 2 Network Response to a) Vessel Power b) Vessel Length and c) Days Absent

Response to days absent during a fishing trip shows both increasing, constant and diminishing marginal returns to time at sea. For the fleet as a whole, it suggests an optimal trip length of around 11 days to maximise profit (at the mean fleet values for vessel length and power). This is somewhat longer than the actual mean of 5.9 days absent,. It may suggest that either current restrictions are already limiting effort below its economic optimum, and/or that catches and revenues are substantially under-declared or recorded (ie balck fish), and that the reality is greater exploitation of the stock for the recorded days absent. Restrictions on days at sea per trip will, however, further reduce catches and vessel incomes/profitability. Network simulation suggests elasticities for vessel power, length and days absent of 0.10, 0.40 and 1.44 respectively.suggesting restrictions on trip length wil have greatest impact on catches and profitability..

4.2 Annual Vessel Effort Model

The optimal neural network model for the vessel annual profit function was an MLP5:4:1, with inputs vessel length, power, GRT, number of trips, average trip duration, 4 hidden layers and profit as the output (Figure 3). The prediction root mean square error of the model was 0.34, approximating to an adjusted coefficient of determination of 0.67. The network weight estimates are presented in Table 5 .

Table 5 Network Weight Estimates MLP 5:4:1 Annual Vessel Profit Model

	h1:1	h1:2	h1:3	h1:4	Threshold
Threshold	-3.30	2.04	-1.60	3.34	
Length	-1.56	-0.36	-0.56	1.04	
GRT	1.34	0.91	-0.80	-0.80	
Power	-0.22	-0.11	0.35	0.74	
Days Absent	-2.39	0.03	0.44	2.75	
No. Trips	4.21	2.80	0.16	5.22	
H : Output	2.98	-3.83	-0.85	2.49	1.80

Responses to the input variables are shown in Figures 4. In general, over the data-set range, the relationships are non-linear with the exception of power, which seems approximately linear. Vessel length and power both positively affect vessel profitability. The former may act as a proxy for auxiliary power, given that deck area may reflect the ability to carry more equipment. Vessel GRT exerts a negative impact on vessel profitability, doubtless through its effect on fuel consumption and hence costs. Response to average trip duration appears logistic in functional form (Fig 4c), and response to trip frequency, approximately quadratic.

Profit-effort elasticity estimates from the MLP network were obtained through simulation. Given the satisfactory explanatory power of this network, these were disaggregated by power size classes and are presented in Table 6. For the fleet as a whole, GRT has a negative and small elasticity, which suggests that decreasing vessel weight will increase overall vessel profitability. The elasticity response to vessel length is 0.85, which suggests that increasing vessel length increases profitability less than proportionately. The engine power elasticity is low and positive.

Table 6 Profit-Effort Elasticity Estimates by Vessel Power Size Groups

Effort Variable	PG1	PG2	PG3	PG4	PG5	Fleet
Length	2.67	0.90	0.52	0.43	0.35	0.85
GRT	-0.23	-0.10	-0.10	-0.14	-0.28	-0.14
Power	0.22	0.17	0.20	0.24	0.41	0.19
Days Absent	2.15	1.37	1.11	0.91	0.64	1.33
No. Trips	1.46	1.05	0.96	0.91	0.76	1.02
Total days	1.76	1.21	1.04	0.91	0.72	1.17

Vessel profitability is highly elastic with respect to days absent at 1.33 and of unit elasticity with respect to the number of trips. This implies an elasticity of 1.17 with respect to total days fishing. It is notable there tends to be a more elastic response of profit to effort in the smaller vessels, and that within power groups 1, restrictions on days from port t will have a significantly greater impact than restricting the number of trips a vessel can make.

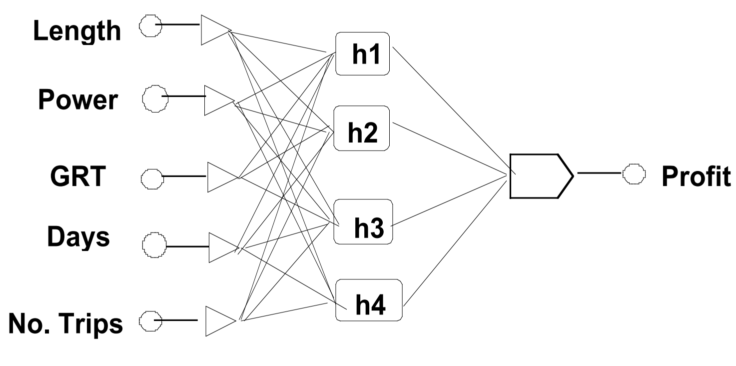

Fig 3 Network Illustration for Annual Vessel Effort Model

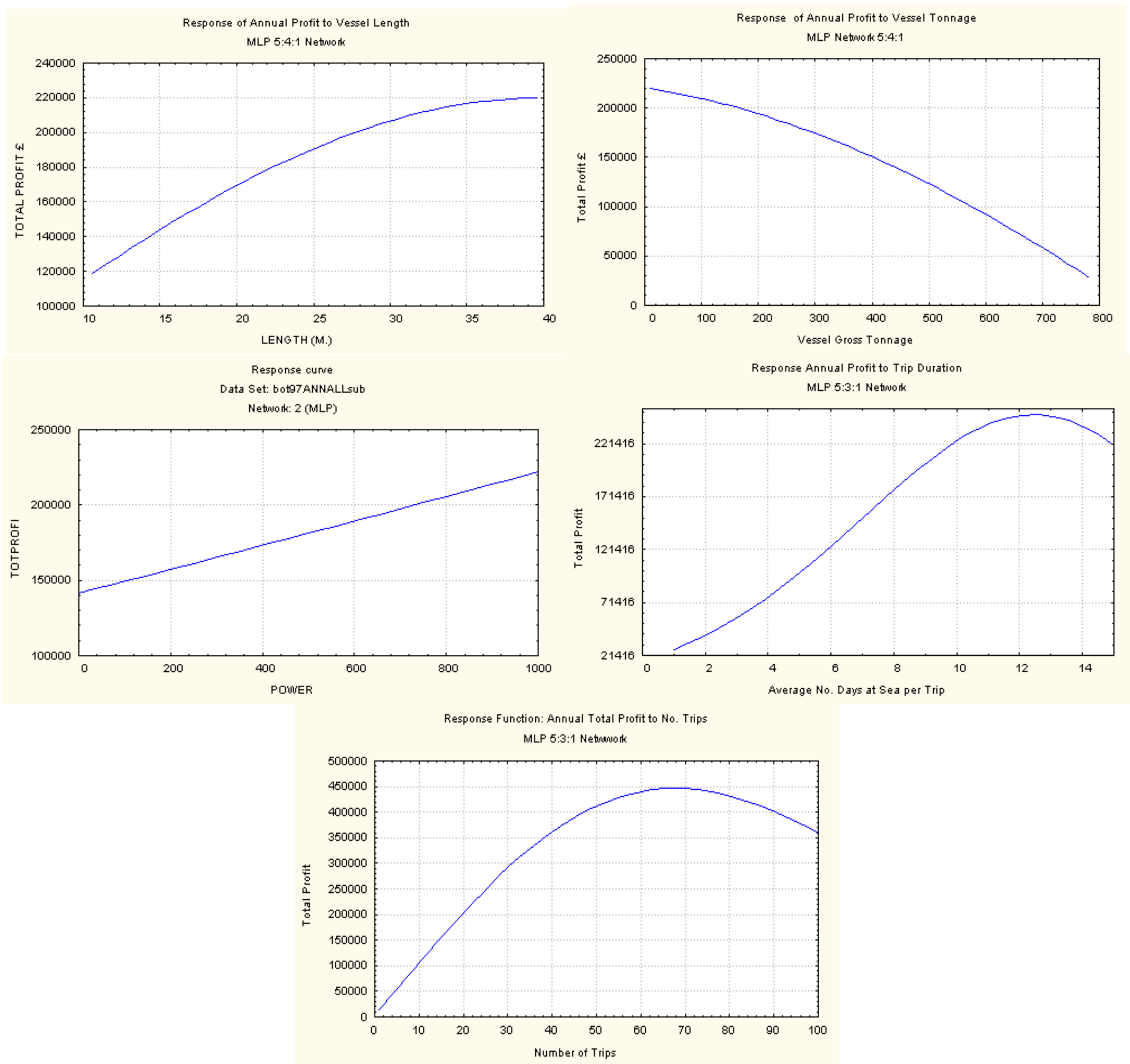

Fig 4. Network Response to a) Vessel Length b) Vessel Gross Registered Tonnage c) Vessel Power d) Vessel Mean Days Absent per Trip and e) No. Trips per Vessel

5. GENERALISED LINEAR MODEL ESTIMATES AND RESULTS

5.1Individual Vessel-Trip GLZ Modelling

A surface functional form was selected a priori as the most appropriate fixed parameter functional form for estimation. This was supported by the response function simulations from neural network modelling, which suggest approximate quadratic relationships between profit and effort variables. However, profit is non-normally distributed, and the most appropriate functional form estimated was that with a gamma distribution for profit and an exponential link function, which were estimated by maximum likelihood. The parameter estimates are shown in Table 7. All parameters other than those indicated are significant at less than the 1percent level. Fit diagnostics show residual deviance to degrees of freedom ratio of 0.4, and the Pearson residuals to degrees of freedom ratio of 0.37, indicating reasonable goodness of fit[7]. All parameter signs are of the expected a priori signs.

[7] Estimation of conventional OLS specification of the same function with no assumption made regarding the distribution of profit, achieved an adjusted R^2 of 0.69

Table 7 GLZ Parameter Estimates for Profit-Effort Surface Function

	Estimate	St. Error
Intercept	3.2604	0.131
Length	0.223	0.020
Length^2	-0.005	0.001
Power	0.003	0.001
Power^2	-2E-06	5.17E-07
Days Absent	0.521	0.018
Days Absent^2	-0.018	0.001
Length*Power	7.6E-05 [a]	3.54E-05
Length*Days Absent	-0.001 [b]	0.001
Power*Days Absent	-0.0002	3.27E-05
Scale	2.558	0.034

Notes: all parameters significant at 1 per cent level except: a. significant at 5 percent level; b. Non-significant
.

The profit-effort elasticities associated with the individual effort variables are presented in Table 8, again disaggregated according to vessel power size groups, given that the surface function produces non-constant elasticity estimates.

Table 8 GLZ Derived Profit-Effort Elasticities for Individual Trips

	PG1	PG2	PG3	PG4	PG5	Fleet
Profit-Length	1.21	0.76	0.07	-0.13	-0.56	0.68
Profit- Power	0.41	0.62	0.55	0.13	-0.59	0.64
Profit-Days Absent	0.97	1.35	1.01	0.45	-0.13	1.30
Harvest-days Absent	0.96	1.32	1.01	0.88	0.77	1.24
Cost -Days Absent	0.84	0.98	1.00	1.01	1.02	0.85

The elasticity estimates are broadly consistent with those presented in Table 6 from neural network estimation, bearing in mind the different data-sets and model specifications. However, the elasticity estimate for power in Table 8 is somewhat higher than in Table 6, but the elasticity estimates of profit to days absent are comparable.

Also presented in Table 8 are the elasticity of cost to days absent, derived from the cost function parameter estimates in Table 3, and the harvest/catch elasticity with respect to days absent. The latter is derived through the profit and cost–days elasticities in Table 8, and the cost and revenue profit shares[8]. The catch-effort elasticity shown in Table 8 is again relatively high for the fleet, and tends to be higher for the smaller vessel power groups relative to the larger vessels. Cost –days absent elasticities on the other hand are higher for the larger vessels.

Models were also specified and estimated to test for different slopes according to power groups, and using power groups as a categorical variable to test for complete or partial interaction with other effort input variables. The results did not improve on those presented above.

5.2 Annual Profit per Vessel GLZ Model

The best estimates for the annual profit-effort model per vessel were achieved through a log link function with linear and quadratic terms for in vessel power, number of trips and average trip length. Parameter estimates are given in Table 9 and the effort elasticities in Table 10. All parameter estimates are significant at the 1 percent level or better and of the expected sign, with ratios of residual deviance and Pearson residual to degrees of freedom ratios both close to 0.17.

Elasticity estimates are reported by power groups and for all vessels. Elasticities again decline as vessel size increases. The elasticities for both numbers of trips and days absent are higher than the equivalent MLP network

---

[8] The catch/harvest-effort elasticity can then be obtained from $\varepsilon_q = (\varepsilon_\pi + \sigma_c \varepsilon_c)/\sigma_r$ where $\_{\pi}$ is the effort elasticity of quasi profit, $\_{q}$ is the harvest elasticity of effort, $\_{c}$ is the cost elasticity of effort , $\_{r}$ is the revenue share of quasi-profit, and $\_{c}$ is the cost share of quasi-profit and in which $\_{r} > 1$ and $0 < \_{c} < 1$.

estimates. However the GLZ model only has power as an additional explanatory variable[9], and so more of the profit response is being loaded onto these two variables.

Table 9 Parameter Estimates GLZ Annual Total Profit Effort Function

	Estimate	Error
Intercept	6.663	0.168
Power	0.001	4.3E-03
Power^2	-5E-07[a]	2.5E-07
Days per Trip	0.697	0.063
Days per Trip^2	-0.034	0.005
No. Trips	0.077	0.003
No. Trips^2	-0.0004	3.1E-05
Scale	5.685	0.493

Notes: all parameters significant at 1 per cent level except: a. significant at 5 percent level; b. Non-significant

Table 10 Annual total Profit Effort Elasticity Estimates

	PG1	PG2	PG3	PG4	PG5	Fleet
Power	0.19	0.36	0.47	0.53	0.24	0.41
No. Trips	1.65	1.48	1.29	1.31	1.14	1.46
Days Absent	1.43	1.75	1.28	1.01	0.75	1.71

6. CONCLUSIONS AND IMPLICATIONS FOR FISHERIES REGULATION

Both neural network and GLZ modelling approaches lead to useful insights into the composition and determinants of efforts in the Scottish demersal trawl fishery where the bottom otter trawl predominates as gear type.

The results have implications for the current proposal to introduce effort controls on vessels operating in the North Sea, primarily as a means of reducing effort on cod stocks and allowing stock recovery. Imposing restrictions on the number of trips or the trip length has a greater than proportional impact on profits in the fishery. With proposed days-at-sea restrictions of up to 60 per cent of the current levels, average "profits" (in fact, average gross margins) of the vessels could decrease by between 80 and 90 percent. When fixed costs are deducted, many vessels are likely to run at a loss.

The results also suggest that a transferable effort quota may be successful, as there are considerable incentives to purchase additional days. As a result, such a policy may result in fleet rationalise in the same manner as would be expected under an ITQ programme.

7. REFERENCES

Bjørndal, T. Production in a schooling fishery: The case of the North Sea herring fishery. *Land Economics* 65: 49-56, 1989.

Campbell, H.F. Estimating the elasticity of substitution between restricted and unrestricted inputs in a regulated fishery: A probit approach. *Journal of Environmental Economics and Management*. 20: 262-274, 1991.

Eggert, H. *Essays on Fisheries Economics*, Ekonomiska Studier Utgivna av Nationalekonomiska Institutionen Handelshögskolan vid Göteborgs Universitet 106, Sweden, 2001.

Greene, W.H., Frontier Production Functions, EC-93-20. Stern School of Business, New York University, 1993.

Herrero, I. and S. Pascoe, Estimation of a composite fish stock index using DEA. Paper presented at the XIIIth Annual conference of the European Association of Fisheries Economists, Salerno, Italy, 18-20 April, 2001.

[9] Parameters for vessel length and /or GRT included in other response and quadratic functions were non-significant.

Kirkley, J.E., D. Squires, and I.E. Strand. Characterizing managerial skill and technical efficiency in a fishery. *Journal of Productivity Analysis*, 9:145-160, 1998.

McCullagh, P. and Nelder, J. A. *Generalized linear models (2nd Ed.)*. New York: Chapman & Hall, 1989.

Pascoe, S. and L. Coglan. Contribution of unmeasurable factors to the efficiency of fishing vessels. *American Journal of Agricultural Economics* 84(3), 45-57, 2002.

Pascoe, S., J.L. Andersen, and J.W. de Wilde. The impact of management regulation on the technical efficiency of vessels in the Dutch beam trawl fishery. *European Review of Agricultural Economics* 28(2), 187-206, 2001.

Sharma, K.R and P. Leung. Technical Efficiency of the Longline Fishery in Hawaii: An application of a Stochastic Production Frontier. *Marine Resource Economics*, 13:259-274, 1999.

Squires, D. and J. Kirkley. Skipper skill and panel data in fishing industries. *Canadian Journal of Fisheries and Aquatic Science*. 56(11): 2011-2018, 1999.