Adaptive Farming Strategies for Dynamic Economic Environment

Nanlin Jin, Mette Termansen, Klaus Hubacek, Joseph Holden, Mike Kirkby

Abstract—This paper aims to forecast the economic impacts of changing land-use in UK uplands. We assume that farmers adaptively learn and respond to a dynamic economic environment. The main research approach is the use of evolutionary algorithms for dynamic optimization. We use this approach to study how the changes of agricultural subsidy policy (CAP reform) affect farmers’ land-use decisions. We compare the experimental results from our simulated evolution versus the predictions made by agricultural experts. We have found that evolutionary algorithms for dynamic optimization forecast farmers’ land-use decision in line with experts’ predictions. This study also shows that maintenance of the diversity of the solution set is important for evolutionary algorithms to continuously track dynamic optimums. This work provides a framework to integrate other natural, social and economic factors in future.

I. INTRODUCTION

The natural and economic environment feature heavily in farmers’ land-use decisions. We have some understanding of the natural environmental [10] and economic factors [3], but how natural and economic environments interactively influence farming remains unclear. In this paper, we study UK uplands considering three types of dynamics: biological dynamics of grouse populations (natural environment); the dynamic grouse prices (economic environment); and government subsidies changing over time (economic environment).

It is well known that government farming policies have great impacts on farming strategies [20] [25]. Reforms of EU (also UK) Common Agriculture Policy (CAP) have recently begun. The aim of CAP reform is to reduce the overall farming subsidy gradually and to motivate farmers to reduce grazing pressure and to promote environmental sustainability. One of the great difficulties for policy makers is to predict the uncertainties of subsequent changes of farmers’ behaviors after the new policy is in place. It becomes especially difficult when the dynamic natural environment interacts with a dynamic economic environment.

We develop an evolutionary algorithms based system to simulate farmers’ decisions in dynamic environments. An evolutionary algorithm (EA) is a population-based meta-heuristic optimization algorithm. The essences of natural evolution, namely selection, reproduction, variation, fitness measures and survival of the fittest are mechanized into evolutionary algorithms [11] [7] [18]. Evolutionary algorithms have successfully solved many classes of problems, including non-linear, epistatic, large search-space and multi-dimension problems [7], [18], [19]. We apply the techniques of evolutionary algorithms for optimization problems in the presence of uncertainties [17]. We execute the evolutionary system. Experimental results help explain how farmers change land use over 30 years. In addition, this study also shows that in evolutionary algorithms, the size of population can help maintain diversity and allow evolutionary algorithms to continue tracking the optimums. This research approach provides an effective way of simulating adaptation in dynamic environments.

This paper is organized as follows: Section II describes the model of the problem. Section III evaluates assumptions of this model. Section IV specifies the evolutionary algorithms (EA) and relevant techniques in evolutionary algorithms to handle dynamics. Section V details the experimental design. Section VI reports the experimental results. Section VII discusses future extensions and finally Section VIII concludes.

II. THE MODEL OF THE PROBLEM

Decision making on land use is economically-motivated. The income from using a farming strategy is often a first priority consideration to most farmers [24]. Farmers are assumed to pursue such a land-use plan that maximizes incomes or minimizes costs.

When farmers make decisions, they must take the dynamics of several drivers into consideration. Dynamics of many drivers increase the complexity of the problem.

A. Grouse Population Dynamics

The number of grouse is naturally varying. Shaw et al [22] analyzed grouse population dynamics in time-series. Hudson et al studied the correlation between grouse population cycles and parasitism [13], [14] and [15]. In this paper, we use the yearly data of the grouse population in Corndavon, Scotland from 1957-1971: (unit: number of grouse ha$^{-1}$) (0.99, 0.89, 1.06, 0.91, 0.86, 1.04, 1.04, 0.94, 1.41, 1.55, 1.31, 1.24, 0.94, 0.82, 1.03) [15]. We assume that the exact same cycle repeats afterwards. It is an approximation to the actual dynamics of grouse population. Figure 1 shows the dynamic pattern over 30 years.

B. Price of Grouse

The price of grouse increases: the price of grouse has increased annually in line with the increase of city salaries [24]. The price of grouse is about £80 per head this year (2007). The average price increase has been 2% per year. We use this increase rate for the 30-year period. No inflation rate is considered in this paper.

Figure 2 shows the increase of grouse price per head over 30 years.

$$p_{y+1} = p_y \times (1 + 0.02)$$ (1)
C. Government Subsidy Reforms

Since 2006, CAP Reform package replaces eleven schemes with the Single Payment Scheme: one new single payment. The aim of this new scheme is to free the subsidies from production and thus reduces the demands of land use for environmentally friendly farming practices [1]. The European Union CAP aims to gradually decouple subsidies from agricultural production and finally abolish subsidies to farmers. It is expected that there is little prospect of financial support after 2013 in the UK [24]. Table I lists the subsidies which farmers receive from 1999 to 2028 on four grazing rates [24][2]. The unit is £. “0.5 sheep ha$^{-1}$” is the grazing density, meaning farmers graze “0.5” sheep per ha in average on their land. The unit of area used in this paper is a hectare (symbol ha). It equals 10 000 square meters. It is commonly used for measuring land area.

Grouse population dynamics, the changing price of grouse and the government subsidy reform increase the complexity of making land-use decision. This paper attempts to understand how such dynamics shape land use.

TABLE I

<table>
<thead>
<tr>
<th>Year</th>
<th>0.5sheep ha$^{-1}$</th>
<th>1sheep ha$^{-1}$</th>
<th>2sheep ha$^{-1}$</th>
<th>3sheep ha$^{-1}$</th>
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<td>5.33</td>
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III. ASSUMPTIONS

We focus on the subsequent land use after the CAP reform. Although many other factors affect the changes of land use as well, we keep other factors static. To this end, we make following assumptions:

1) The market price of lamb is static: £15. This price is an approximate average price in recent years [24]. Making the market price static, we simplify the market dynamics, ignoring changes of demand (such as customers’ preferences) and of supply (such as imports).

2) The physical environment remains unchanged. We assume physical environment remains stable over the 30-year in question.

3) We focus on five popular farming strategies on UK uplands. This is mainly because according to statistical data for UK upland farming, the major farming strategies have been grazing and game keeping [4]. Game keepers take care of heather, grouse population and grouse hunters. Game keepers’ major income comes from selling shot grouses. For grazing, we study four types of grazing rates which are widely used on UK uplands, namely 0.5 sheep ha$^{-1}$ (or per ha), 1 sheep ha$^{-1}$, 2 sheep ha$^{-1}$ and 3 sheep ha$^{-1}$. 

where $p_{y+1}$ is the grouse price in year $y + 1$ and $p_y$ is the grouse price in year $y$. 

\[ p_{y+1} = \frac{p_y + 1}{2} \]
4) We pay attention to sheep grazing, not cattle grazing. Firstly, the number of cattle is much smaller compared to the number of sheep on upland areas. Secondly, most uplands are graded on disadvantaged land or severely disadvantaged land according to HFA 2007 [2], therefore it is neither profitable nor sustainable for grazing cattle [9].

5) We assume that the labor costs of the five farming strategies are about the same. The costs of equipment and facilities of different farming strategies considered in the paper vary slightly [24]. We ignore such differences.

6) We assume the yearly farming cycle is as follows: at the beginning of a year, a farmer starts with investigating possible land-use plans and predicts the potential incomes of these plans. The farmer chooses the highest rewarding plan and farms as the chosen plan. By the end of the year, the farmer checks the income from this land-use plan and the change(s) of landscape if any. Next year this process repeats.

7) We assume that it is cost-free to change from one land-use plan to another. In addition, we assume the production is irrelevant to farmers’ experiences, to how long a land-use plan has been applied or to the current land-use situation.

8) The time period we study is 30 years, from 1999 to 2028.

9) We assume the land is suitable for both grouse shooting and grazing.

10) We do not consider economic inflation.

IV. RESEARCH APPROACH

The dynamics are always difficult to handle. Due to dynamics, the optimum changes over time. An ideal approach for such problems would track the optimum continuously. Evolutionary algorithms are one of such approaches which have addressed optimization problems with uncertainties [6]. Evolutionary algorithms simulate natural evolution [12]. Natural evolution is a continuous process to adapt to uncertainties and dynamics. Jin and Branke comprehensively review how evolutionary algorithms solve optimization problems in the presences of uncertainties [17].

The characteristic for evolutionary algorithms handling dynamic environments is that its fitness function $F(x)$ is time-varying, dependent on time $t$. $X$ is a vector of parameters. As the $f_t(X)$ is varying subject to time, evolutionary algorithms track the changing optimum continuously.

$$F(X) = f_t(X)$$

(2)

Co-evolutionary algorithms are also featured by their time-varying fitness functions [18] [16]. The difference is that $F(X)$ above is independent of the evolving population(s), while the fitness functions for co-evolutionary algorithms are evolving too.

In the farming model in Section II, the fitness of a farming strategy has no connection with the change of land-use plans in previous years. So we use the technique of evolutionary algorithms for dynamic environments. One way to cope with dynamics in evolutionary algorithms is to treat any change of fitness as the start of a new optimization problem. When the fitness function change is radical and the new optimum is far from the optimums before a radical change, restart is a good solution [17]. However, this technique does not suit our the problem because all three dynamics considered in this study are supposed to change gradually rather than abruptly. In the evolutionary process, we therefore use another technique: to maintain (part of) individuals survived in previous generations and revalue parental individuals after any change [23].

As the existence of dynamics, we must take into account the diversity of the population during the evolutionary process. It is believed that a diversified population adapts to changes more quickly with less efforts whereas a converged population usually needs longer evolutionary time and more efforts to adapt to changes [17]. So in this study, we must make sure that the diversity is sufficient for finding out the new optimum efficiently. A typical way to generate diversity is to increase the mutation rate. The mutation rate can be increased greatly just after a change [5], increased gradually [26], or kept high. As the properties of the problem characterize the potential changes continuously, we adopt a relatively high mutation rate which remains static during the evolution process.

V. EXPERIMENTAL DESIGN

This section specifies the design of the experiments. The main method to tackle this problem is evolutionary algorithms. We detail the strategy representation, EA set up, fitness function and evolutionary process.

A. Strategy Representation

A farming strategy refers to one of the five options: (1) grouse shooting; (2) sheep grazing 0.5 sheep ha$^{-1}$; (3) 1 sheep ha$^{-1}$; (4) 2 sheep ha$^{-1}$ and (5) 3 sheep ha$^{-1}$. In some cases, farmers distribute two or more strategies on their land, each strategy applied on a proportion of their 100-ha. Therefore, it is necessary to design a land-use plan as a mixed strategy

The mixed strategy determines the distribution of the five farming strategies. We can easily use integer strings to represent the mixed farming strategies. So we use Genetic Algorithms (GA) [11] [7] to evolve mixed farming strategies. A mixed farming strategy $(x_0, x_1, x_2, x_3)$ interprets how 100 ha of land is used: $x_0$ ha for grouse shooting; $x_1$ ha for gazing 0.5 sheep ha$^{-1}$; $x_2$ ha for gazing 1 sheep ha$^{-1}$; $x_3$ ha for gazing 2 sheep ha$^{-1}$; the rest of land $100 - x_0 - x_1 - x_2 - x_3$ is for gazing 3 sheep ha$^{-1}$. Figure 3 gives an example of a mixed farming strategy $(24, 32, 10, 3, 31)$. It shows that 24 ha for game keeping; 32 ha for gazing 0.5 sheep ha$^{-1}$; 10 ha for gazing 1 sheep ha$^{-1}$; 3 ha for gazing 2 sheep ha$^{-1}$; $100 - 24 - 32 - 10 - 3 = 31$ ha is for gazing 3 sheep ha$^{-1}$.

1 The mixed strategy here is different from the mixed strategy defined in Game theory [21].
B. GA set-up

The parameters of the GA set-up are in Table II. The set of candidate solutions (mixed strategies) is called “population” in terms of GA. We select GA strings for reproduction by using 3-member tournament selection. Three GA strings are randomly selected and the string that has the highest fitness is selected for reproduction. Two selected GA strings produce two new GA strings by one-point crossover: two selected GA strings are divided at the crossover point. Then the first proportion of one string is swapped with the first proportion of another string. The newly generated two strings will be members of the population of the next generation after mutation. One-point mutations happen at a low mutation rate. One point of a GA string is altered by another value. In order to satisfy the constraint of the GA representation:

\[ x_0 + x_1 + x_2 + x_3 \leq 100 \]

any replaced value of the mutation point must be less than the value to be replaced. For example, in Figure 3 the GA string [24, 32, 10, 3] is mutated at the point with the value of 32. If the newly created value is larger than 32, the mutated GA string will not satisfy the constraint. If the value is less than 32, the constraint will be satisfied and 100 - (x_0 + x_1 + x_2 + x_3) will change accordingly. Any one mutation results in the changes of two strategies (namely the mutated point and the 100 - (x_0 + x_1 + x_2 + x_3)), although the GA string is only modified one point. The mutation rate is the probability of a crossover GA string mutates. As Section IV has discussed, we use a high mutation rate to maintain diversity throughout the evolutionary process.

![GA String](image)

**Fig. 3. GA representation**

C. Fitness Function

The fitness function \( F(x) \) measures the income of using a mixed strategy \( x \).

\[
F(x) = \sum_{i=1}^{5} (x_i \times I_i)
\]  

where \( x \) is the land plan or the mixed farming strategy:

\[
x_{mn} = \begin{bmatrix} x_0 \\ x_1 \\ x_2 \\ x_3 \\ 100 - x_0 - x_1 - x_2 - x_3 \end{bmatrix}
\]

\( I \) is the income matrix of a mixed strategy. \( s_n \) is the subsidy for grazing \( n \) sheep ha\(^{-1}\):

\[
I = \begin{bmatrix} p_y \times d_y \\ s_{0.5} + 0.5 \times b \\ s_1 + 1 \times b \\ s_2 + 2 \times b \\ s_3 + 3 \times b \end{bmatrix}
\]

and

\[
b = r \times (1 - k) \times I
\]

The fitness value \( F(x) \) of a GA string \( x = (x_0, x_1, x_2, x_3) \) is the sum of the income from grouse shooting \( x_0 \times p_y \times d_y \), the income from grazing with 0.5 sheep ha\(^{-1}\) \( x_1 \times (s_{0.5} + 0.5 \times b) \), the income from grazing with 1 sheep ha\(^{-1}\) \( x_2 \times (s_1 + 1 \times b) \), the income from grazing with 2 sheep ha\(^{-1}\) \( x_3 \times (s_2 + 2 \times b) \) and the income of grazing 3 sheep ha\(^{-1}\) \((100 - x_0 - x_1 - x_2 - x_3) \times (s_3 + 3 \times b)\).

**Table III**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>y</td>
<td>year</td>
</tr>
<tr>
<td>( p_y )</td>
<td>the price of grouse in year y</td>
</tr>
<tr>
<td>( d_y )</td>
<td>the number of grouse in year y, ( d_y \in D )</td>
</tr>
<tr>
<td>b</td>
<td>income of selling lambs at the grazing density 1 sheep ha(^{-1})</td>
</tr>
<tr>
<td>l</td>
<td>the market price of lamb</td>
</tr>
<tr>
<td>k</td>
<td>flock replenishing rate</td>
</tr>
<tr>
<td>r</td>
<td>lambing rate</td>
</tr>
<tr>
<td>s_{0.5}</td>
<td>subsidies for grazing 0.5 sheep ha(^{-1})</td>
</tr>
<tr>
<td>s_1</td>
<td>subsidies for grazing 1 sheep ha(^{-1})</td>
</tr>
<tr>
<td>s_2</td>
<td>subsidies for grazing 2 sheep ha(^{-1})</td>
</tr>
<tr>
<td>s_3</td>
<td>subsidies for grazing 3 sheep ha(^{-1})</td>
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</table>

\( r \) is the lambing rate which is 77% [9]. \( k \) is the flock replenishing rate of the all lambs produced on the year \( k = 0.32 \) [9]. So \( r \times (1 - k) \) is the number of lamb produced for market. \( l \) is the market price of lamb. We use the average price £15. 0.5, 1, 2 and 3 sheep is the number of sheep, including ewes, hoggs and rams.

The income from grouse shooting is the outcome of dynamic grouse prices \( p_y \) and of dynamic grouse number \( d_y \). The grazing income is determined by the income from selling the lambs \( b \) and by government subsidies \( s_n \). Figure 4 illustrates the fitness of each of five farming strategies over 30 years. From this figure, we can see that farmers who graze 0.5 sheep ha\(^{-1}\) always have the lowest income.
The income $x_0 \times p_y \times d_y$ from grouse shooting in year $y$ is the outcomes of dynamics of grouse prices $p_y$ and of dynamic number of grouses $d_y$. The grazing incomes are determined by the income from selling the lambs $b$ and by government subsidies $s_y$. CAP reform starts 2006 as year 8 on this figure and ends 2013 as year 16 on this figure.

Before CAP reform, government subsidy policy heavily favored farmers who produced more lambs. From Figure 4, the subsidies were five to six times more to farmers who grazed 3 sheep ha$^{-1}$ than those farmers who only grazed 0.5 sheep ha$^{-1}$. The subsidies were 2 times and 4 times more to farmers grazing 1 sheep ha$^{-1}$ and 2 sheep ha$^{-1}$ respectively than farmers grazing 0.5 sheep ha$^{-1}$. The subsidies were so high that they were nearly the same as farmers’ income from selling lambs. For example, a farmer grazing 1 sheep ha$^{-1}$ could expect to sell 0.41 lamb per ha to the market, in return the farmer received about £6.15 per ha. On the other hand, the farmer received a subsidy of £5.66 which was almost 92% of the income from lambs. For a farmer grazing 2 sheep ha$^{-1}$, the subsidy was 87% of the income from lambs. These figures tell us that subsidies from government were one of main sources of incomes for farmers who use their land for grazing. The subsidies were a strong economic incentive for farmers to stock as much as possible. This was a threat for sustainable land use.

During the transformation of CAP reform, the impacts of government subsidies are complicated. The introduction of a Single Payment Scheme increased farmers’ income enormously in 2006 and then a year after, the subsidies decrease linearly to no subsidies in 2014 at all. Government policy only gives a few years for farmers to adjust their farming strategies. Interestingly, during the CAP reform period, farmers who graze at the low grazing rate, 0.5 sheep ha$^{-1}$ receive no subsidies at all because the minimum stocking rate is one sheep ha$^{-1}$ for receiving subsidies. So, farmers grazing at low densities are under more severe economic pressure to quit grazing.

After CAP reform, there will be no subsidies available for sheep grazing. As a result, farmers’ income will totally rely on the income from selling lambs. It is clear that to graze 3 sheep ha$^{-1}$ will be the most rewarding choice. In addition, compared with any time before the end of the CAP reform in year 2014, any grazing strategy will receive less income especially when using higher grazing rates, simply because of the withdrawal of subsidies. From 2014, farmers who graze 1, 2 and 3 sheep ha$^{-1}$ will get £5.33, £10.66 and £16 less than before the CAP reform. If a farmer wants to receive a decent income from grazing, he has to maintain a high grazing density. Also, any fluctuation of the market prices of lamb causes uncertainties of farmers’ incomes. Unlike grazing, game keepers for grouse shooting receive increasing incomes. Although grouse cycles naturally vary, the steady increase of grouse prices gives game keepers a prosperous future. Game keepers receive no subsidies from government, therefore their decision making does not directly connect to CAP reform. However, there is an incentive that farmers who used to graze sheep may convert their land for grouse shooting in future, with potential environmental impacts as grouse rearing is associated with vegetation burning.

This fitness function is complicated, consisting of three types of dynamics. The next section will report how evolutionary algorithms track the optimum of this dynamic fitness function over time.

D. Evolutionary Process

As we assume in Section III, farmers will take another mixed strategy if the new mixed strategy is expected to bring higher income in the following year. Farmers’ land use decisions are adaptive to the economic environment and farmers continue trial-and-error learning.

The evolutionary system simulates a farmer’s decision making process. The system starts with a set (population) of mixed strategies. The farmer chooses the highest rewarding one and applies it to his land at year $t$. A year after (year $t + 1$), the farmer compares the actual income of using this mixed strategy at year $t$ with the possible incomes of other mixed strategies according to his expectations of year $t + 1$’s grouse numbers, the grouse price and subsidies. The farmer chooses the highest rewarding one among them as his decision of land use for year $t + 1$.

We explain now how the evolutionary system adapts to the dynamic fitness function. At every year (generation), the mixed strategies in that population are evaluated against the fitness function $f_t(X)$ for that particular year $t$. Note that the fitness function is time-varying, so the same mixed strategy may have different fitness values in year $t$ from its fitness in year $t + 1$.

VI. EXPERIMENTAL RESULTS

We have evolved mixed farming strategies to adapt to dynamic grouse population, dynamic price of grouse and changing sheep subsidy. We have found that farming strategies evolve to cope with such dynamics.
A. Changes of Farming Strategies to CAP Reform

Experimental results from the evolutionary system are shown in Figure 5, 6 and 7. Before CAP reform (Year 1 to Year 7 in these figures), and during CAP reform (Year 8 to Year 15), the farming strategy of grazing 3 sheep ha$^{-1}$ has been always the most favored choice, in terms of income. After CAP reform (Year 16 and beyond), the farming strategy of grouse shooting gradually becomes the ideal one with the highest income amongst five strategies. Sheep farming is not completely disfavored though.

From the farming perspective CAP reform will effectively reduce the grazing pressure in long term and encourage other ways to support the regional economy.

B. Experimental Results versus Expert Assessment

Agricultural scientists examined “market-led” scenarios to predict changes caused by CAP reform [4]. They established baseline conditions, mapped from existing land use and land cover databases, and then translated scenarios into spatially explicit adjustments to the baseline. Under “market-led scenario”, CAP reform results in “80% reduction in sheep numbers on moorland” and “10% decline in livestock units/unit area across all grass and rough grazing” [4]. Sotherton et al. [24] found that due to the annual increase of the price per grouse brace, the potential to operate game keeping for grouse shooting “is quite feasible” in long term. These predictions from agricultural scientists and farming experts are in line with our experimental results from the evolutionary system.

C. Evolutionary algorithms for dynamic optimization

We have tested the evolutionary system with different crossover rates, mutation rates, inserting different number of random individuals into new population at every generation [8] and different population sizes. We have found that the size of population is very important in maintaining diversity for continuously tracking the optimum in dynamic environments.

We will demonstrate below how the size of population affects the experimental results. We will show experimental results of three different population sizes while maintaining a relatively high mutation rate, see Table II.

1) Large population size 100000. Figure 5 shows the mixed strategies over 30 years from the evolutionary system with a population size of 100000. Grazing 0.5, 1 and 2 sheep ha$^{-1}$ occupy a very small amount of land, less than 20 ha in every 100 ha. Grazing at the highest grazing rate: 3 sheep ha$^{-1}$ occupies 80 to 90 % of land before Year 22$^{th}$. After that the strategy of grazing 3 sheep ha$^{-1}$ dominates other strategies at year 20, 24, 29 when its fitness is the highest. However, in Figure 6, the grazing of 3 sheep ha$^{-1}$ is still dominated by grouse shooting during year 24 and 29 when the grazing 3 sheep ha$^{-1}$ gets the highest fitness.

2) Middle population size 1000. Figure 6 shows the mixed strategies over 30 years from the evolutionary system with a population size 1000. Grazing 0.5, 1 and 2 sheep ha$^{-1}$ only occupy a small amount of land, less than 30 ha in every 100 ha. Grazing at the highest grazing rate: 3 sheep ha$^{-1}$ occupy 50 to 90 % of land before Year 15. After that grouse shooting and grazing 3 sheep ha$^{-1}$ alternatively dominate the landscape. Grouse shooting becomes important after Year 15 when CAP reform ends. From this figure, the impact of CAP reform on land use can be observed as the subsidies changed to the point where the grouse shooting and grazing 3 sheep ha$^{-1}$ have very close fitness. When the income difference between grouse shooting and grazing 3 sheep ha$^{-1}$ becomes slim during year 15 to 22, the experimental results of the evolutionary system with the population size 1000 fail to respond to the fitness changes immediately. There is a tendency to continue the previous year’s mixed strategy. It is evidenced by the fact that in Figure 5, the grazing of 3 sheep ha$^{-1}$ dominates other strategies at year 20, 24, 29 when its fitness is the highest. However, in Figure 6, the grazing of 3 sheep ha$^{-1}$ is still dominated by grouse shooting during year 24 and 29 when the grazing 3 sheep ha$^{-1}$ gets the highest fitness.

3) Small population size 100. Figure 7 shows the mixed strategies over 30 years from the evolutionary system with a population size 100. Before the end of CAP reform, i.e. year 15, the strategy of grazing 3 sheep ha$^{-1}$ is slightly better than others. After the end of CAP reform, from year 17, the grouse shooting is absolutely dominant choice. Even during year 17 – 20, 24 and 29 when the grazing 3 sheep ha$^{-1}$ has the highest fitness values, the evolutionary system with the population size 100 still prefer the grouse shooting.

From Figure 5, 6 and 7, the mixed strategies from the evolutionary system with a population size 100000 reflect the
dynamic optimums promptly, even to slight environmental changes. In contrast, the mixed strategies from the evolutionary system with a population size of 100 smooth out minor environmental changes. Continuously tracking the dynamic optimums is computationally costly. The evolutionary system with a larger population size searches a larger search space and requires more computational resources. The evolutionary system with a smaller population size requires less computational resources, so it can not always track the dynamic optimums immediately, especially those dynamic optimums which last for a short period of time. These trade-off rules help users of evolutionary systems determine when to employ a small size of population and when to employ large size of population.

Different mixed strategies are generated by these three evolutionary systems with different population sizes. As in reality, facing the same economic dynamics, farmers may choose different mixed strategies due to different knowledge, experiences and other considerations. An experienced farmer can better evaluate the best choice. Both knowledge and experiences are learned, for which time and effort are needed.

VII. Future Work

The model we have studied in the paper is a simple one, which mainly focuses on economic impacts on land use. We are considering a more sophisticated and complicated system which not only takes other economic impacts into consideration but also studies natural environments, such as biophysical, bio-diversity and hydrological environments.

As known, these natural environments are full of dynamics and uncertainties [10]. Figure 8 illustrates a conceptual structure on which social-economic environments interfere with natural environments.

![Fig. 8. Our planned integrated system for rural economy and land use modelling](image)

We will extend the evolutionary system that we have established in this paper. We will include impacts of the natural environment into the fitness function. This fitness function will be dynamic over time and dependent on the mixed strategies of the previous year(s). Hopefully the extended system will tell more interesting stories about land use and more about dynamics in an evolutionary system.

In addition, in this model no extreme case is studied. Figure 5, 6 and 7 show that for relatively long periods of time, a single farming strategy dominate a large proportion of the land use and other farming strategies are actually discarded. Using a single farming strategy (or a corner solution) is vulnerable to unpredictable scenarios. If on a farm, game keeping was the only farming strategy during 2006, it could be vulnerable. For example, there could be a grouse disease or bad weather which destroyed the grouse population. Therefore it is important to consider diversified mixed strategies to avoid catastrophic outcomes by extreme scenarios. We will examine this in future.

VIII. Conclusions

This paper studies land use management through simulated evolution. We assume the adaption of farmers’ decision making can be captured by evolutionary algorithms. The dynamics of grouse population, the price of grouse together

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with the changes of government subsidies greatly increase the complexity of farmers’ decision making.

We establish an evolutionary system using evolutionary algorithms and techniques of EA for dynamic environments. This system searches adaptive farming strategies over time. Experimental results have shown that the optimal farming strategies under the three dynamics vary over time with everything else being stable. The dynamics force the evolutionary system to adapt accordingly. We have found that the CAP reform reduces grazing and encourages game keeping for grouse shooting in long term. This finding is in line with the predictions made by agricultural experts. It is hoped that results from using evolutionary systems provide indicative information of future land use for government agencies and other environmental organizations. Advised by findings, government agencies can readjust farming subsidies and policies to protect uplands farming and environments better.

From the viewpoint of evolutionary algorithms, another important finding is that the population size of the evolutionary system is important in maintaining diversity of the population and thus makes the optimum tracking easy in the presence of the time-varying fitness function. Certainly, to run an evolutionary system with a larger population size requires more computational resources than to run such a system with a smaller population size.

We understand the model studied in this paper is simple. We will consider enlarging the evolutionary system to incorporate the dynamics of natural and economic environments. This study has provided a solid ground for future extensions.

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