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# An Investigation into the Use of the Temporal Scan Statistic as a Monitoring Tool for Health Impact Assessment

A thesis submitted to the

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for the degree of

Doctor of Philosophy

Elaine Hand

Department of Public Health & Primary Care

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Elaine Hand

November 2005

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## Summary

Health impact assessment (HIA) is an important methodological development within public health. Its purpose is to ensure that health is considered as a part of all government proposals and policies. While there has been substantial development of the HIA methodology within the last 10 years, the issues associated with monitoring health events at the end stage of an HIA have not received appropriate attention. This aspect of HIA is vital to the success of HIA as it ensures that any negative impact on health is detected as soon as possible after the implementation of a programme or policy.

In order to effectively monitor events within a HIA process an appropriate method needs to be utilised. The temporal scan statistic is a method that has been used for the detection of clusters. It has not been utilised as a monitoring tool or used to detect dips as opposed to clusters but as there are a number of versions of the scan statistic, it does offer adaptability to cope with different data issues.

The main aims of this thesis were to investigate if it was feasible to monitor health events within a HIA and to assess the effectiveness of the temporal scan statistic as a monitoring tool. A number of case studies were utilised in order to thoroughly investigate these aims.

The scan statistic was found to be a highly competent monitoring tool in all the case studies considered. In the cases where it was of interest to monitor a negative health impact such as looking at tram accidents, cancer cases near an incinerator or clusters of suicide the scan statistic efficiently identified increases in events. On the other hand when it was of interest to monitor positive health impacts the scan statistic detected decreases in respiratory deaths after the bituminous coal ban and

decreases in road deaths following the introduction of penalty points for speeding. In the case of penalty points the scan statistic also detected the increase in road fatalities a few months after the initial decrease.

These examples showed that post-implementation monitoring is a vital stage in a health impact assessment. It has been shown to be important to monitor both positive and negative health consequences. By monitoring health events in this way the unforeseen can be detected and addressed in a timely manner.

In this research, the scan statistic has been shown to be an effective monitoring tool. It is flexible enough to cope with different types of data, including health outcomes that are rare and data that have strong seasonal or trend components. A power analysis was undertaken in order to demonstrate the efficiency of the scan statistic for this purpose. The binomial scan statistic was found to be the most efficient version of the scan statistic, both in terms of ease of application and accuracy.

This research indicates that monitoring is an essential component for all HIAs and that the temporal scan statistic offers an efficient and flexible tool to employ in such circumstances. It is recommended that a monitoring tool such as the temporal scan statistic is implemented within HIAs.

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# Chapter 1

# A Review of the Use of Statistics in Health Impact Assessment

## 1.1 Introduction

> Health impact assessment is a combination of procedures, methods and tools by which a policy, program or project may be judged as to its potential effects on the health of a population.
>
> - World Health Organization [1]

Health impact assessment (HIA) is a widely researched area that has been shown to have many benefits. HIA research has concentrated on the social aspects such as community involvement and awareness. HIA has not been examined or assessed to any great extent from a statistical viewpoint. There is an obvious gap in HIA development in terms of sound statistical tools and methods. There is a lack of statistical know-how in the implementation of HIA and hence there is a lack of

evidence of its success.

This thesis examines the use of the scan statistic as a monitoring tool. The scan statistic can be used temporally, spatially or spatio-temporally; this thesis will concentrate on the temporal form of the scan statistic. The use of the scan statistic specifically for the monitoring of health events and specifically in a HIA environment will be examined. Furthermore, the statistical requirements of monitoring a HIA will be outlined and an appropriate method will be suggested.

An important stage of a HIA is the monitoring and evaluation phase. However, little research has been done to suggest how health effects can be monitored post implementation of a policy. Indeed there is little emphasis on the importance of monitoring health effects. Using the scan statistic, health effects could be monitored easily, this would mean that negative health impacts are highlighted quickly, while positive health effects are also recognised thus highlighting the positive impact of a new policy.

Health impact assessment methodology will be explained and examples of where it has been applied highlighted. Using these examples, the lack of appropriate statistical methods will be discussed. The areas in a HIA where different statistical tools would be appropriate to use will then be considered. In Chapter 2 the scan statistic methodology will be explained in detail and different versions and applications of the scan statistic will be explained through applied examples. Chapter 3 and 4 will see the application of the scan statistic as a monitoring tool to appropriate HIA examples. Initially, cases where a negative impact on health is observed or expected, and then to where a positive impact is expected and so monitoring for a decrease in adverse health effects is necessary. Finally, the power of the scan statistic as a monitoring tool will be assessed.

## 1.2 Health Impact Assessment

Health impact assessment is an analysis that is carried out to see how a policy, program or proposal may impact health, and to then capitalise on findings by minimising any of the negative impacts and enhancing any positive impacts on a population. It is a combination of methods with the aim of assessing the health consequences of a policy, project, or program that does not normally have health as its primary objective.

### 1.2.1 Why do a Health Impact Assessment?

Governments are composed of many different ministries. Each ministry is concerned with one specific concern relating to the population, be it finance, employment, agriculture, children etc. This may make for an efficient government. However, problems arise when the actions of one ministry affect another ministry. For example, supposing in the ministry of finance it was decided to increase taxes on farming land, this could impact the ministry of agriculture and perhaps the ministry of employment. Health is one of many issues that cuts across the concerns of different ministries.

The health consequences of progress and its consequent increase in exposure to various pollutants are often of great interest to the public and at the same time public awareness about potential environmental hazards is growing. Recently there have been cases of objections raised to proposed landfill sites in Cork, Tipperary and Waterford [2], where the impact on health and the proximity of the proposed sites to residential areas provided concern.

There are other proposals that the general health of the public does not influence.

A planned dual carriageway route from Athlone to Kinnegad was revised, the refined route addressing "...engineering concerns as well as economic, environmental and social objections ..." [3] . Health concerns were not included in the plan for the new road, yet new roads can lead to more traffic which could lead to a higher incidence of noise pollution, air pollution, traffic accidents and road rage, all of which can have an impact on health.

Health impact assessment aims to identify possible hazards to health, as well as highlighting potential benefits. HIA puts health at the forefront of any decisions or policy making, this ensures that health is considered by all sectors and departments and not just health related areas.

### 1.2.2 The History of Health Impact Assessment

Environmental impact assessment (EIA) was introduced because the decision tools used in the planning of large developments only took into account financial cost and failed to accommodate issues affecting the environment or bio-diversity. In 1969, the Environmental Protection Act [4] was introduced by the United States - this required an EIA of all projects in the United States of America and of overseas projects that were funded by the USA. The European Commission followed suit with a 1985 directive [5] by requiring that all large-scale developments are subject to an EIA. In 1992 the Environmental Protection Agency [6] was established in Ireland to oversee EIAs in Ireland.

The importance of human health issues in an EIA was realized at an early stage [7]. A recognition of the wide range of factors that can impact health, and the importance to health of non-health policy areas led to calls for healthy public

policy [8] and by implication health impact assessment of policies.

Health impact assessment has been used internationally. Its early use was confined mostly to aid programs in developing countries. Now its presence is felt in many countries world-wide, including:

- United Kingdom [9, 10]
- Australia [11, 12]
- Canada [13, 14]
- Sweden [15].

### 1.2.3 The Structure of a Health Impact Assessment

The structure of a HIA is important and it insures some degree of quality and comparability between HIAs. Perhaps more important than the HIA method are the people who should be involved in a HIA.

Obviously it would be sensible to include the proposal decision makers in the HIA. They will be fully informed of the proposal and should be able to provide details on all aspects of the proposal which would be important for HIA. There will also be a public health doctor who will be aware of different health effects. It is crucial that a HIA expert is involved in all stages of a HIA to ensure that the correct procedures are followed, this means that the HIA is thorough and that it will be comparable to other HIAs.

As HIAs are often carried out at community level the inclusion of appropriate community groups will not only provide valuable insight into the community but it will also give the community a sense of ownership of the HIA and proposal.

This ensures that the HIA is seen to be at ground level and not something carried out by government officials who may be thought of as somewhat removed from the actual community. With the right structure in place the actual format of a HIA is standard across all types of HIA.

There are three different formats employed in a health impact assessment:

1. Prospective health impact assessments attempt to predict the outcome of a policy not yet implemented and can be based on the experience of similar decisions in the past

2. Retrospective health impact assessments look at the effects of policies or programs that have already been implemented

3. Concurrent health impact assessments happen at the same time as a policy is implemented and the consequences of the policy are monitored as it is implemented

It is accepted that a prospective health impact assessment is the ideal form of a HIA as any negative effects will be highlighted and changes to a proposal can be made in sufficient time to reduce the possibility of negative effects. With a retrospective health impact assessment, negative impacts to health will already have occurred and it can be difficult to "undo" some policies or programs that have already been implemented. In a concurrent health impact assessment appropriate adjustments can be made to the policy to ensure that negative health impacts are reduced. However, as the policy or program has been initialized a complete reversal of the policy might prove to be problematic.

No matter which format of HIA is selected the general method or process of the HIA will be similar. While different organisations have different matrices

and tools for conducting HIAs, all HIAs follow a similar set of stages. The five main stages to health impact assessment are screening, scoping, appraisal, decision making and, evaluation and monitoring.

### 1. Screening

Not all policies, programs or projects may require a health impact assessment. At the screening stage of a HIA such policies or programs can be filtered out. The health impact of a certain policy may already be well documented; in this situation it would not be sensible to expend resources collecting evidence for something that is well documented. During the screening phase it may also be decided that a particular proposal has a neutral or negligible impact on human health; in such a case it may be decided that a full health impact assessment is unnecessary.

Screening should be conducted systematically using a set of criteria against which proposals can be judged, it is useful in the screening phase to use a tool such as 'The Health Question' which is outlined in the appendix(Figure A.1 on page 144). A robust screening stage will ensure that scarce resources are targeted towards proposals that will benefit most from a HIA. For selected proposals the screening stage can provide an important foundation for the conduct of further stages in the HIA.

### 2. Scoping

The second stage in a health impact assessment is scoping; here the terms of reference for the HIA are set. It could be thought of as an administrative 'working-out' phase of the HIA. The following items should be addressed during a HIA [16]:

- Elements of the proposal to be assessed - it may not be feasible to address all elements of a proposal so only the vital parts should be assessed
- the proposal's non-negotiable aspects - it is important to have a list of 'must dos' to ensure that the most important and perhaps impacting aspects are addressed
- aims and objectives of the HIA - while this may seem obvious, it is important to know the purpose of the HIA
- values underpinning the HIA
- the populations or communities affected by the proposal implementation - especially any vulnerable, marginalized, or disadvantaged groups within the affected population/community
- the geographical area covered
- potential health impacts of concern
- background information for the HIA (evidence base, HIAs of similar proposals, baseline profile of the population/community, and specific local conditions affecting proposal implementation)
- methods to be used during appraisal or risk assessment
- timescale for the HIA - again this is important in a prospective HIA to ensure that the HIA is completed before implementation of the proposal
- management arrangements
- work programme

- resources available and required - in terms of human, financial and material
- decision-making forums that may be influenced
- arrangements for the monitoring and evaluation of the HIA and its outcomes.

The scoping stage is extremely important in setting down the boundaries in a HIA. While many of the items such as management arrangements and resources available may be the same from one HIA to the next it is still vital that these items are discussed in the scoping stage.

**3. Appraisal**

Appraisal is also referred to as 'Risk Assessment'; it is the third major step in a HIA. The aim of the appraisal stage should be to estimate the potential of a proposal to affect the health of a population once it has been implemented. Potential positive or negative health impacts can be identified here using quantitative or qualitative methods.

At this stage the use of statistical methods is important in order to assess positive or negative impacts on health. Decision analysis and modeling tools can be essential here to aid the evaluation of health impacts, these will be discussed in some detail later in this chapter. Cluster analysis methods such as the scan statistic can also be useful here to investigate clusters of specific health events resulting from a particular proposal.

**4. Decision Making**

This fourth stage of the health impact assessment involves the consideration of the appraisal and then choosing the best option from the given information. The best option may be the decision of no-action or it may include variations on the original proposal and ways to minimize possible disadvantages and enhance any possible advantages to the publics health.

Once a decision has been made it is important that a report is prepared and that the necessary recommendations are made. The report and recommendations need to be submitted to decision makers within the decision makers time frame, ensuring that they meet deadlines for scheduled meetings about the proposal. Although the report and recommendations will be produced primarily for the decision makers it is important to disseminate the main findings of the report and recommendations to all stakeholders. It is important that the content, format and presentation of the communication is designed according to the needs of the stakeholders and their preferred way of accessing information.

**5. Evaluation and monitoring**

Evaluation or implementation outlines the procedure required to implement the policy and evaluates the health impact assessment. The evaluation of the HIA process is an important source of learning. It is part of the drive towards quality improvement and is also vital in quality assurance. Monitoring evaluates the acceptance and implementation of recommendations; were recommendations followed through? - Why? or Why not? It would be naive to assume that all recommendations in a HIA were automatically implemented. The results of a HIA

are only one of many different factors that will influence decision makers and the resulting proposal.

Monitoring is vitally important where harmful consequences may have been predicted but where their exact nature is unclear. This stage will also monitor and evaluate indicators and health outcomes after a proposal has been implemented. Monitoring will also detect any unforeseen adverse outcomes, and modifications can be made to the policy in order to minimize all the adverse consequences. Monitoring of health effects can be fraught with difficulty as often the predicted health effects cannot be monitored using routine data. In cases where the health effects can be monitored then proper monitoring charts need to be available. An appropriate monitoring method using the scan statistic will be discussed in this thesis.

All of the examples of health impact assessment that were examined use different tools and different matrices [17, 15, 13, 18, 19, 12]. Two examples of these tools are illustrated in Appendix A. However, they all follow a similar method based on the five stages previously discussed. They all begin with a screening phase where a policy is examined and it is decided if a health impact assessment will be carried out. They do this either by using a series of set questions or by meeting with stakeholders and discussing the issues. They then progress to the scoping stage where they decide what data are needed, what resources will be needed, what areas should be studied and who should implement the study. The various health impacts are then examined and somehow a decision is made as to whether the impacts are positive or negative and how much they will affect the population in question. It is at this stage that the different health impact assessment methods differ. In some situations there are no clear guidelines as to how any decision

should be made regarding impacts. What is done if there is a strong negative health impact? What is considered a strong health impact? Does it mean deaths? Does the new policy need to impact a certain proportion of people? What about a slight inconveniencing health impact? In other cases there are clear guidelines set down as to what should be done.

### 1.2.4 Where should Health Impact Assessment be used?

There are many topics that can be subject to a health impact analysis. It could be decided to implement health impact assessment for certain policies, or for all policies - excluding unsuitable policies in the screening phase. Examples of where health impact assessment has been used include:

- Expansion of gambling [20]
- Area renewal housing strategy [21]
- Grounding of an oil tanker [22]
- New roads, bypasses or freeways [23, 24]
- Landfill site [25]
- Development of an airport. [26]

#### Prioritization

Health impact assessment could also be used as a prioritization tool. At the Copenhagen Consensus [27] a number of the world's problems were discussed, solutions

to the world's problems such as hunger, disease, trade barriers and water were analyzed and a cost benefit analysis was carried out to assess the profitability or the 'best value for money' of each proposed opportunity. Each of these solutions was then ranked by nine leading economists from around the world, and a prioritized list was drawn up of the top ten problems and solutions that should be given financing. The list was prioritized according to the cost benefit analysis and it is shown in Table 1.1

| Ranking | Challenge | Opportunity |
|---|---|---|
| 1 | Diseases | Control of HIV/AIDS |
| 2 | Malnutrition | Providing micro nutrients |
| 3 | Subsidies and Trade Barriers | Trade Liberalization |
| 4 | Diseases | Control of Malaria |
| 5 | Malnutrition | Development of new agricultural technologies. |
| 6 | Sanitation and Water | Small-scale water technology for livelihoods. |
| 7 | Sanitation and Water | Community-managed water supply and sanitation. |
| 8 | Sanitation and Water | Research on water productivity in food production. |
| 9 | Government and corruption | Lowering the cost of starting a new business. |
| 10 | Population Migration | Lowering barriers to migration for skilled workers. |
| 11 | Malnutrition | Improving infant and child nutrition. |
| 12 | Malnutrition | Reducing the prevalence of low birth weight. |
| 13 | Diseases | Scaled-up basic health services. |

Table 1.1: Expert's Prioritization List

Running parallel to the Copenhagen Consensus was a Youth Forum[1], representing postgraduate students from 80 countries around the world. The Youth Forum was charged with the same task as the experts, they were to prioritize the world's challenges and opportunities. The Youth Forum was made up of postgraduate students from many disciplines including social sciences, politics, law, business and the health sciences. The students' prioritized list is in Table 1.2.

| Ranking | Challenge | Opportunity |
|---|---|---|
| 1 | Malnutrition | Investment in technology in developing country agriculture. |
| 2 | Disease | Scaled up basic health services. |
| 3 | Governance and Corruption | Grassroots monitoring and service delivery. |
| 4 | Education | Holistic education model. |
| 5 | Conflict | International peace fund. |
| 6 | Sanitation and Water | Community managed low cost water supply. |
| 7 | Financial Instability | Change governance structure of World Bank. |
| 8 | Subsidies and Trade Barriers | A balanced Doha Round. |
| 9 | Climate Change | Kyoto Agreement. |
| 10 | Population Migration | Active immigration policies. |

Table 1.2: Youth Forum Prioritization List

As is evident from the tables the prioritized lists are very different. The economists—being economists—prioritized according to the cost benefit analysis, and their prioritized list shows solutions that will give the 'best value for

[1]The author was selected to represent the European Union at the Copenhagen Consensus Youth Forum

money'. The Youth Forum expressed difficulty with the prioritization process, indeed there was much consternation within the proceedings. Many of the delegates at the Youth Forum argued that the cost benefit prioritization did not consider 'happiness' or 'value of life'. This very different attitude of the Youth Forum is reflected in their prioritized list.

It has been argued by Professor Bjorn Lomborg, organizer of the Copenhagen Consensus, that prioritization is a tool by which to compare and contrast problems. Cost-benefit analysis is as good a tool as any other to use for this prioritization process and Professor Lomborg has argued quite correctly that 'we can't do everything, so what should we do first'. However, health impact analysis could be utilized here. Instead of prioritizing by cost efficiency, prioritization could be done by, for example: number of lives saved or incidence of disease reduced. Indeed it is possible that other parameters such as happiness or quality of life could be incorporated and a tool such as one of the HIA matrices outlined in Appendix A could be utilized.

The idea of health impact fits perfectly with the concept of prioritization. The purpose of health impact assessment is exactly represented by the quote at the beginning of the next section which is similar to the goal of the Copenhagen Consensus; both are ideas with the aim of eradicating inequality in the world. All of the challenges addressed at the Copenhagen Consensus have a direct impact on health so it makes sense that a health impact assessment be used to prioritize the challenges and solutions. Furthermore, not all of the challenges could be represented meaningfully by a cost benefit analysis. For example the challenge of global warming is a long term problem, an expensive problem to tackle and the returns are not great but it is something that impacts health. Similarly all of the

other challenges could easily be prioritized in terms of health.

### 1.2.5 Health Impact Assessment in Ireland

> [HIA] is designed to ensure that all policy makers, especially those more indirectly involved in the health system, consider the impact that their decisions might have, both directly and indirectly, on the health of the population.
>
> -Irish National Health Strategy [28]

One of the goals of the Irish National Health Strategy [28] is to ensure that the health of the population is at the centre of public policy. Health impact assessment is a relatively new concept in Ireland, but it is something that is receiving keen interest and will be in practice shortly. It has already been implemented in Northern Ireland on a number of projects [29]. The All-Ireland Institute of Public Health has published a number of introductory reports and held a number of workshops on health impact assessment [30, 31, 32]. The response to HIA in Ireland has been enthusiastic; the only questions a number of people have about it are "when can I do one?" or "where can I try this out?".

In Ireland there are numerous situations where HIA could have been applied. There has been discussion of proposals for a new runway in Dublin airport; this is something that could be suitable for a HIA. A similar assessment was carried out previously in Manchester when the airport was extended [26]. There are many issues that would need to be considered: for example the noise level for local residents, traffic disruptions that could lead to excessive stress on commuters. A full health impact assessment would highlight all possible impacts of a new airport

on the health of the public, and it would also be important to consider the health impact while construction work was in progress.

A more topical and controversial issue is that of waste disposal. There have been numerous cases in the last year of residents objecting to proposed landfill sites in Waterford, Tipperary, Galway and Laois [2] among others. One study of a proposed landfill site in Galway examined the following areas before rejecting the site: landscape, land use, ecology, archaeology, geology and hydrogeology, traffic, road access, haul distance and development costs [33]; the health of local residents was noticeably absent.

In Galway there has been controversy over a halting site for Travellers, which is located close to a closed landfill site at Carrowbrowne, Co. Galway [34]. Had Galway Corporation carried out a health impact assessment on the location of the halting site then perhaps a different location or option for the halting site could have been chosen and the subsequent High Court case avoided.

There have been heated debates about the proposed incinerator for Cork Harbour, with many objections from local residents. If a HIA is carried out, it may help to ease some of the fears that the residents have. If they are aware of all the procedures in place to minimise health impacts, and are reassured that their health will be monitored closely to ensure that there are no negative impacts, this may help to allay any concerns.

In the case of landfill sites and incinerators a HIA is necessary prior to the final proposal, as it should highlight any health issues that may arise from the location of the site. If the assessment is carried out in the initial stages of the proposal a more suitable location for the landfill site can be found, if necessary. This would help to reassure concerned residents that all precautions with respect to health are

guaranteed.

In order for health impact assessment to be effective it should be a multidisciplinary process, within which a range of evidence about the health effects of a proposal or policy is considered, within a structured framework. The potential health impacts of a proposal can be analysed and used to influence the decision making process [35].

## 1.3 Statistics in Health Impact Assessment

### 1.3.1 Possible Benefit of Statistical Tools

In their assessment of the health impact of the Sea Empress oil spill, Lyons et al. carried out a survey of residents living in urban locations near to the site of the oil spill [22]. The residents were asked for any symptoms they felt after the oil spill and these results were compared to a similar town that was not near the oil spill location. They found that there was an increase in reported prevalence of headaches, sore throats and sore eyes. However in this study the distance from the oil spill was not investigated, i.e. if individuals living further away suffered fewer symptoms. Lyons et al. [22] stated that little was known about long-term health effects of the oil spill, and there does not seem to have been a follow up to this study. In this study there was an obvious lack of the monitoring of health impacts even though concerns over long term impacts had been stressed.

A rapid HIA of foot and mouth disease was carried out in Devon [36], England. The study group looked at various issues such as economic and, policy and social issues; the main health effects studied were mental health and respiratory

problems due to the pyres. The study group carried out qualitative research and found that there was a risk of increased suicide among farming groups, especially given the evidence [37] to suggest that farmers rank fourth among occupational groups with respect to suicide. They found no significant impact on health services due to the pyres and increased respiratory problems. Gastro-intestinal illness was highlighted as a potential result of the contaminated water supplies associated with the pyres.

The group did recommend that general practitioners (GPs) monitor health service utilization in selected areas. However the group did not recommend how the various health effects should be monitored. They also recommended that a further health impact assessment should be carried out one year after the foot and mouth outbreak. If an efficient monitoring system were in place any unusual clustering of disease or syndromes could be detected at the earliest moment. If there was a clustering of mental health problems then extra resources could be provided to help the communities cope with the aftermath of the foot and mouth disease. While it is suggested that GPs monitor their service utilization, this will not give an indication of service utilization in the whole area.

A HIA was carried out to look at crime prevention [38]. Crime and burglary can have a detrimental effect on the physical and mental health of the victim. The first crime prevention strategy involved securing households with extra locks, alarm systems and new windows and doors. The HIA was assessed by qualitative means. The health impacts were found to be mostly positive. However there were some negative impacts reported in other areas due to fear that criminals would choose another perhaps easier target. A monitoring system could have been incorporated with the qualitative assessment which would monitor numbers

of burglaries and the initiative could then be judged successful if there was a significant dip in crime levels. If the monitoring system incorporated a spatial aspect a shift in the target area of criminals could be detected in good time and new strategies put in place.

These examples show where a HIA could have benefited from some sound quantitative analysis or a follow-up monitoring system. While these examples show where HIAs may have been lacking in certain aspects, there has been some use of statistics in HIA.

### 1.3.2 Statistics in HIA

A number of quantitative approaches to health impact assessment have been developed; these are mathematical models for impact analysis. These quantitative models include PREVENT [39], POHEM [40], Global Burden of Disease [41], and ARMADA [42, 43].

#### PREVENT

PREVENT is a mathematical model which was developed by Gunning-Schepers in 1988. It is a cell-based simulation model that can be used to estimate the health benefits for a population when there are certain changes in risk factor prevalence due to trends and interventions over a maximum period of 50 years. The model can be applied in terms of proportional changes in disease specific incidence and in terms of absolute changes in such parameters as disease specific and total mortality.

The PREVENT model was used to assess the health impact of increased physi-

cal activity on coronary heart disease in England and Wales [39]. For the purposes of the PREVENT model the authors assumed that there was an inverse graded relationship between coronary heart disease risk and physical activity; the hypothesis that had been proposed by Shaper [44]. Two strategies were modelled: the first was a 25 per cent increase in the proportion of adults who were moderately active, the second was a similar increase in the proportion that was vigorously active. The modelling indicated relatively small reductions in coronary heart disease death rates. However the health impact was greater for the proposal of increasing moderate activity: a 0.15 reduction in coronary heart disease deaths over 25 years. The model could also show that targeting behaviour change in males over 45 years of age who already took some form of physical activity would provide the greatest population benefit.

The PREVENT model is limited to applications involving health promotion interventions and as such is fairly limited in its application to HIA.

**POHEM**

POHEM [40] is a longitudinal microsimulation model which was designed by the Health Analysis and Modeling Group of Statistics Canada to simulate the health status of the Canadian population. Among the data it incorporates are data on risk factors, disease onset and progression, and health outcomes. It currently models breast cancer, lung cancer, coronary disease, arthritis and dementia.

The POHEM model creates synthetic populations at birth and provides them with demographic and labour force characteristics, such as age at marriage, number of offspring, employment income and divorce. By using simulation techniques POHEM ages these individuals while exposing them to risk factors and diseases.

It can therefore be used to reproduce individual characteristics for a population and generate longitudinal data for a representative sample of a generation. POHEM can be used to evaluate the impact of different risk factors, to assess diagnostic and therapeutic options for lung cancer and to evaluate the costs of care for this disease. Various cost parameters can also be estimated.

The model was used to estimate the direct medical costs of current practice and new treatments associated with lung cancer in Canada [45]. They found that the direct medical cost of lung cancer and treatment was just over CAN$528 million. They also estimated that the cost per year of life gained as a result of treatment of the disease was approximately CAN$19,450. The authors concluded that the treatment of cancer was affective from a purely economic viewpoint.

THE POHEM model could be applied in HIA and could be a successful prediction model for HIA. However, at present the POHEM model is limited by Canadian data, but it is a good basis for a more global HIA simulation package.

**Global Burden of Disease**

The Global Burden of Disease (GBD) [41] has been developed by WHO over the past decade. The concept of disease burden can be thought of as "a systematic and internally consistent quantification of health problems of a defined population, preferably using a summary measure of population health that integrates mortality and morbidity information" [41]. Research on the burden of disease can provide a sensible basis for implementation and policy development, so it seems logical that studies on the burden of disease form the basis of health impact assessment research. The primary activity of the GBD has been the development of comparable, valid, and reliable epidemiological information on a wide range of

diseases, injuries and risk factors.

De Hollander et al. [46] applied the GBD approach in the Netherlands and identified a number of environmental hazards for which there was reasonable data relating to public health outcomes. The number of cases of each disease was identified and these were converted to disability-adjusted life years (DALY) by estimates of severity and duration. The results provide a sense of relative impact for different environmental factors such as water supply and hygiene, occupational environment and pesticides. The health loss attributable to environmental exposures was found to be relatively small in the Netherlands. Given that the total annual burden of disease is estimated to be approximately 2.5 million DALYs, in the Netherlands [47] less than 5% of this disease burden could be attributable to environmental exposures (excluding accidents). However this figure rises to 12% when accidents are included.

This method is confined to HIA's looking specifically at disease, so it is limited as a quantitative HIA method. Any HIAs dealing with disease incidence would benefit from including this method among their tools in the HIA.

**ARMADA**

ARMADA [42, 43] is the only one of these four mathematical models that has been specifically developed for health impact assessment. The model is based on people moving between different health states until they die. For a given population the model uses mortality and morbidity statistics to calculate baseline age and sex hazard functions. The relative risks, of different levels of exposure to environmental changes, are incorporated into the model and health status of the population in the presence of the environmental development is calculated.

The ARMADA model was applied to a scenario where a new incinerator was proposed for a town on the south coast of England [43]. The population in close proximity to the incinerator was approximately 10 000. Using data drawn from the environmental statement on expected levels of emissions and traffic, and also data on the wind-plume population for air and chemical exposure, and the city population for traffic exposure, the extra disease for the incinerator was estimated to be '0.15 of a person' in 30 years. This figure contrasts with a total mortality over the whole period of perhaps 60 000 people. It is therefore a low extra level of death.

There are problems with some of the models outlined above. For example there is little understanding of the implication of extrapolating risks between different populations. McCarthy and Utley [43] stress that the estimates of air pollution used in the ARMADA model are based on US data during the 1970s-1990s. Also, impacts may vary greatly between different social groups and this is not accounted for in the above models. Any other health impacts, aside from disease, cannot be accommodated by the above models.

However, even given the limitations of the models that have been discussed, a rough quantitative estimate of a health impact is intuitively more appealing to policy makers than a qualitative approach, which could perhaps be considered 'wishy-washy'. Quantitative measures of health impact assessment provide a means by which different proposals can be compared effectively and efficiently using bottom line numbers such as number of deaths or disease. It is this type of evidence that appeals to policy and decision makers.

All of the models discussed above will aid the decision making process and help in identifying the best proposal in terms of health impacts. However, mon-

itoring tools are vital once a proposal has been implemented to ensure that the health impacts remain positive.

### 1.3.3 Discussion of Lack of Statistical Evidence

Parry and Stevens [48] assessed some of the problems that could be associated with the current health impact assessment structure as outlined in section 1.2.3. They highlighted the issue of ineffectual literature reviews and a number of HIAs that have been carried out did not give an explicit description of the review process, which could mean that most HIAs have not been informed by a systematic review of evidence. According to Perry and Stevens these flawed reviews are likely to result in "... biased and inaccurate effect estimates" [48].

The next vital part of the health impact assessment is consultation with stakeholders. Parry and Stevens [48] stressed the importance and benefits of this step, but they advised caution in the analysis and collection of such data. Any consultations that are carried out need to be performed with extreme stringency in order to achieve a balanced view.

With the above issues in mind Parry and Stevens emphasised the need for empirical tests of the predictive process. A number of HIAs that have been executed have been prospective, indeed it is recommended that if at all possible a HIA should be prospective. However, this requires some sort of follow up. As stated by Isson [49] "the monitoring of health trends and outcomes will probably be conducted by officers in an organization or partnership and incorporated into existing systems for data collection and monitoring".

It is evident from all the resource articles and web sites dedicated to HIA that

the focus has been very much on the policy and political aspect of health impact assessment. Current literature goes far in inventing and describing new models to carry out health impact assessment. However, these models are all similar in nature and they appear to mostly outline the roles of different people involved in a health impact assessment, how much time and money it should cost, and what policies or programs require a HIA.

An enhancement which has not been used in health impact assessment to date but which was suggested by McIntyre and Petticrew [50] is a method to compare quantitatively the different effects of policies. Decision analysis and systems for weighting evidence have been proposed for environmental impact assessment [51], but it has not been looked at in relation to health impact assessment.

The Vizayakumar and Mohapatra assessment [51] examined the consequences of the unchecked use of potentially harmful technology using a method known as cross impact simulation. They looked at how different variables, such as pollution, affected population, social pressure, level of use of technology, health care, pollution control pollution taxes and additional expenditure impacted each other. They developed a matrix which showed the positive or negative impact that the variables had on each other. Using this they then simulated various models using a program in Fortran77. For example for a very basic model they took the case where the unabated use of potentially harmful technology is dumping pollutants into the environment. It was obvious from the simulation that this scenario increased the affected population. They also looked at the other variables and examined how changes in these variables would affect the model.

A similar method applied in the health impact assessment situation could be very useful. It would mean that a lot more options, with respect to the policy that

is under analysis, could be tested with little effort required. It would also mean that the best possible option could be chosen.

In short, current models of health impact assessment tell us what it is, who should be involved, how long and at what cost. However there has not been enough work focused on how any analysis should be carried out. It would be possible to gather all the right stakeholders and have the necessary resources and still not know the best approach to analyzing the data.

It is clear that a set of analysis tools is needed in order for health impact assessment to achieve it's maximum potential. Any methods that are used would need to included a temporal aspect, as this has a heavy bearing on health; carrying out a health impact assessment based on a single point in time does not make a lot of sense in most situations. The health of all individuals changes over time and it is usually a cumulative effect over time that will impact a persons health, so constant monitoring of appropriate health factors is required.

Another significant aspect to be considered is a spatial impact. When carrying out a health impact assessment it is usually in order to identify the impact of something such as a landfill site or new road on the individuals living in the surrounding areas, so obviously spatial analysis is important. How far away from residential zones does a landfill site need to be located in order not to impact on health? Or what is the best route for a new road to take so that it maximises a commuters' comfort and minimises the local residents' health risks.

Figure 1.1 outlines the health impact assessment procedure as explained previously. It also suggests where statistical tools should be used and how they should be used at each stage. In the screening phase, decision analysis tools could be used as an aid to decide if a health impact assessment is necessary. Decision analysis

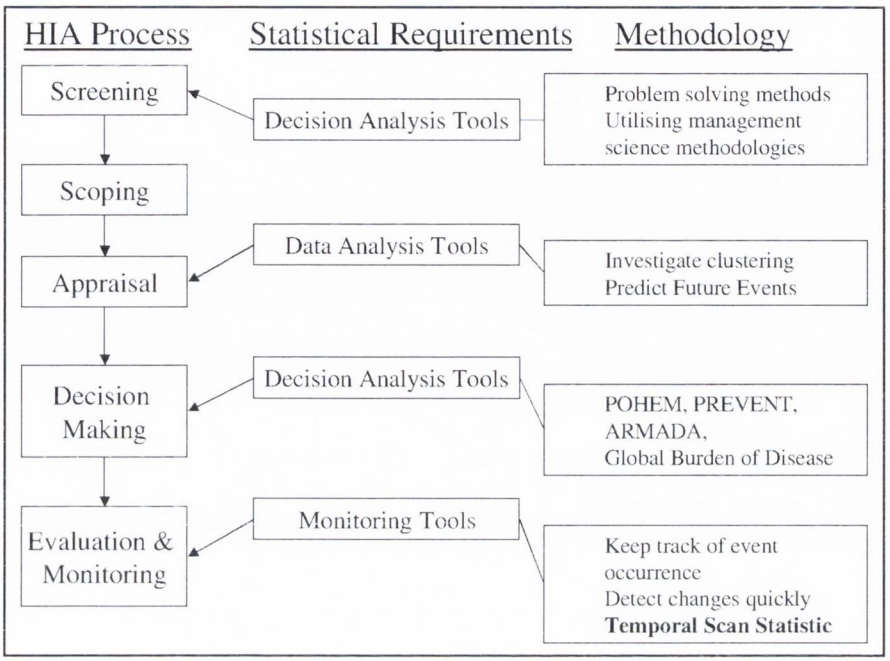


Figure 1.1: Proposed Statistical requirements in a Health Impact Assessment

tools, such as those discussed in section 1.3.2 could be used again in the decision analysis phase - at this stage decisions have to be made as to what extent a new policy should be implemented. Decision analysis tools, such as linear programming methods, would help in weighting the important aspects of the policy, thus ensuring a minimum of negative impacts on health.

In the appraisal phase of a HIA data analysis tools would need to incorporate spatial, temporal and spatial-temporal aspects. In some circumstances when the health impact assessment is prospective, then predictive aspects of the data analysis tools would be important.

A recurring point at the 5th Annual UK and Ireland HIA conference [52] was the lack of a monitoring and evaluation phase in health impact assessments, and the importance of the monitoring and evaluation phase. The monitoring and evaluation stage has two different interpretations:

**Monitor the Progress** of the health impact assessment process and after a health impact assessment has been implemented evaluate how well it was implemented, or

**Monitor the Health Effects** to observe positive or negative impact of the change.

The WHO defines monitoring as: "...the periodic oversight of a process, or the implementation of an activity, ..., so that timely action can be taken to correct the deficiencies detected." [53] This definition of monitoring is rarely implemented in a HIA. The monitoring phase of a HIA is essential to ensuring that any ill-effects are highlighted immediately and positive health effects are likewise emphasized.

The scan statistic [54] would be useful and could be applied in a health impact assessment. It involves scanning the data with a moving window and attempts to detect a tendency of events (e.g. deaths) to cluster. A simple image of the scan statistic is that of a person sitting on a train looking out the window, the train is moving and so the window has a constantly changing view. If the person is a farmer they may be interested in the largest number of cows in a field - the largest number of cows the individual sees from the window at any one time could be considered a cluster of cows. In the case of the scan statistic a rather arbitrary window is moved over a time series of data, the largest cluster of cases is of interest and indicates a tendency of the events to cluster. The scan statistic will be discussed in more technical detail in Chapter 2.

There has been some development of the scan statistic as a tool for detecting clustering in space and time. Using these developments the scan statistic could be implemented in the appraisal phase. The scan statistic is very flexible and will be useful in retrospective situations, but it can also be used as a predictive tool and therefore it would be essential in prospective or concurrent HIAs. The scan statistic is adaptable as a monitoring tool; monitoring of health events could be carried out in the appraisal stage - if the health impact assessment was retrospective a retrospective scan could be used.

## 1.4 Aims and Objectives of the thesis

The aim of this thesis is to evaluate and assess the scan statistic as a monitoring tool in health impact assessment. The objectives are:

- to investigate the feasibility of a monitoring tool in health impact assessment;
- to test the temporal scan statistic under different scenarios;
- to assess the use of the scan statistic as a monitoring tool;
- to compare different versions of the scan statistic;
- to investigate the use of the scan statistic for detecting dips in events

**Specific Test Applications**

- to assess the impact the penalty point system is having on road fatalities;

- to assess if the bituminous coal ban had a positive impact on respiratory deaths;
- to investigate if there is any evidence of copycat suicides in Ireland;
- to monitor the impact of a new tram system on a city's population;
- to investigate monitoring of cancer cases in the vicinity of an incinerator.

## 1.5 Conclusion

The method of health impact assessment has been discussed in detail. The need for statistical methods, specifically monitoring tools, has been highlighted; this has been confirmed with some examples of HIAs where monitoring tools or statistical tools could have helped the health impact assessment by providing evidence of health benefits or negative implication.

Given the lack of evidence of any monitoring being undertaken as part of a health impact assessment, it seems that work is required in this area. The next chapter will outline the requirements of a statistical monitoring tool, and the technical aspects of the scan statistic will be discussed. In following chapters the appropriateness of the temporal scan statistic as a monitoring tool, especially for use in a health impact assessment will be considered and illustrated.

# Chapter 2

# The Scan Statistic

## 2.1 Introduction

Chapter 1 explained where health impact assessments lacked vital statistical input. This chapter will look at different means of filling the gaps in health impact assessment by using appropriate statistical tools. As monitoring tools have been largely neglected, this thesis will focus on their use in a health impact assessment.

## 2.2 Statistical Methodology for Health Impact Assessment

HIAs are usually implemented by public health practitioners or by local community groups. Therefore in order to encourage the use of statistical methods they need to be easy to implement and easy to understand.

As HIA covers a very broad spectrum of problems, it will consequently lead to a broad spectrum of data types, and with that issues with data quality. It is impor-

tant that the monitoring tool is flexible and does not place numerous constraints and assumptions on its use, so that it can be applied in different situations where there are distinct data problems. In the monitoring phase of a prospective HIA, the tool should have the capability to alert to increases or decreases in the occurrence of events. In a retrospective HIA, where a particular programme has had an impact on health, then the particular tool will need to be competent at assessment of clusters retrospectively.

The purpose of monitoring for health effects is to alert to an increase in health impacts in a timely manner. It is important, therefore, that the selected method is time efficient and alerts to increases or decreases quickly.

If a certain planned programme is thought to have a positive impact on health then it may be of interest to monitor for a decrease in health events. By showing that a particular programme reduces certain health events, and by having statistical evidence of such a decrease, it lends credence to the programme which could then be implemented elsewhere. It also lends credence to the HIA method - this will help with future funding for HIAs and ease the implementation of future HIAs.

## 2.3 Monitoring Tools

An important aspect of monitoring is that the tool can take account of overlapping time periods. For example suppose that over a 5-year period 1991 to 1995 there are 19 reported cases of cancer. Within this five year period suppose that eight of the cases fall within a one year period ($13^{th}$ April 1993 to $13^{th}$ April 1994), it might be of interest to know if this cluster is unusual; in other words given that 19 cases occurred in 5 years, how unusual is 8 cases in one year?

A traditional way of solving this problem might be to divide the five years up into five disjoint one-year periods, and look at the distribution of the maximum number of cases falling in any one year. However the cluster will not be detected using this method as the eight cases fall between two disjoint years. The traditional method of cluster analysis uses disjoint time periods as found in a calendar. The scan statistic moves away from calendar time periods and analyzes the data as one continuous time period rather than the specified years or months.

## 2.4 Scan Statistic

The scan statistic is a method that is used to examine clustering of events over time, space or both time and space. The method involves the scanning of data with a window, in search of either the largest number of events in that window, or the data may be scanned looking for the smallest window that contains a pre-specified number of events.

If a large cluster of events were observed over a period of time it would be of interest to know whether the cluster was unusual or due to random factors. Clusters do occur naturally and not every cluster will be significant or due to some external reason. The scan statistic is a method that can be used to test whether a cluster is unusual by looking at the relative frequency of large clusters assuming that the events are randomly independently distributed.

The following example clearly illustrates the scan statistic. Each point on the line represents a case of Spina Bifida in the period 1997-1999. The shaded area within the box represents a window scanning the data. As the window moves across the time line the number of cases of Spina Bifida within each window is

counted. The maximum number of cases is then assessed using one of the methods to be discussed in the following sections.

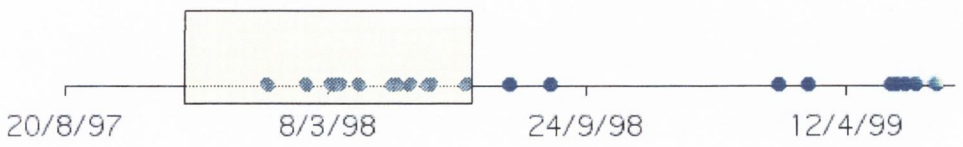


Figure 2.1: Spina Bifida Cases in Ireland, 1997 - 1999

### 2.4.1 Where has the Scan Statistic been used?

The scan statistic has been utilized in a wide variety of areas that include digital screening [55] and genetics [56], public health, epidemiology and veterinary medicine [57]. The scan statistic has also been used in other fields such as actuary studies, where it was used to examine occurrences of clusters of threshold exceedances by the individual claims [58]. It has been used in physics to examine gamma rays and cosmic ray data [59]. The US Department of Justice has researched the possibilities for using the scan statistic to look at clusters of crime [60]. The use of the scan techniques generally falls under one of the following headings: temporal, spatial and spatio-temporal.

In a temporal setting the scan statistic has been utilized as a surveillance tool in a poison control centre, where clustering of carbon monoxide cases were found

using a temporal scan method [61]. This was the only evidence of the use of the temporal scan statistic that could be found.

A spatial scan statistic based on the Bernoulli model was used to investigate if there was clustering of bovine tuberculosis in Argentina [57]. It was also used to investigate spatial differences in breast cancer incidence in Connecticut, USA [62]. Clustering of childhood astrocytoma in Sweden was investigated and while an increase in incidence was observed there was no significant clustering [63]. An investigation of the distribution of BSE in Switzerland was carried out with the use of a spatial scan statistic: clusters of BSE were located in eastern and western Switzerland [64].

A spatio-temporal method was used to investigate clustering, over time and space simultaneously, of acute respiratory disease in Norwegian cattle herds [65]. A space-time scan statistic which adjusted for confounding factors was used to examine clustering of Blowfly strikes in sheep flocks in Australia [66]. To assess whether an observed excess of brain cancer in Los Alamos, Mexico was a real cluster, confounding factors such as preselection bias and multiple testing could be accounted for by using a space-time scan statistic [67].

Clustering of suicide in the US Marines was investigated. Clustering over time and space was found to be ambiguous while overall suicide rates were lower than expected, and there was clustering of suicide among ethnic male groups [68]. Research was carried out to investigate if there was any clustering of symptomatic human pesticide exposures and significant spatial and temporal clustering was revealed [69]. Turnbull examined spatial and temporal clustering of leukaemia in New York [70] using the scan statistic.

While there have been many applications of the scan statistic in a spatial and

spatial-temporal environment as a temporal monitoring tool it has yet to be thoroughly assessed. The health impact assessment environment is a challenging opportunity to investigate the appropriateness of the scan statistic as a temporal monitoring tool. There are many opportunities for monitoring in HIAs: the scan statistic could be used to monitor disease, suicide and road accidents among many other important health impacts.

The scan statistic is a relatively innovative tool, it has been developed and utilized, particularly in recent years. However, the scan statistic has not been utilized to any great extent as a monitoring tool. As was outlined in Chapter 1, there is no evidence of monitoring of health effects in HIA, even though it is purported to be one of the most necessary stages in a HIA. The scan statistic would appear to be an efficient monitoring tool, specifically because it is quite a versatile tool.

## 2.5 Methodology

There are different versions of the scan statistic, and depending on the data available, either the binomial scan statistic, the scan statistic on the circle, the Poisson scan statistic or the ratchet scan statistic may be used.

To efficiently explain and illustrate each example, Spina Bifida data will be used. Spina Bifida is a congenital anomaly; it is the medical name given to a birth defect in which the spinal column fails to form properly while the baby is developing in the womb. It is the most common of the 'neural tube defects'. The causes of Spina Bifida are thought to be environmental and genetic. Lack of folic acid, and incinerators have been linked to Spina Bifida. It is therefore a useful

illustrative example. The data are from the period 1997 - 1999 (see figure 2.4, page 35).

In all of the examples in this chapter a scanning window of 91 days or three months will be used. A scanning window of this length is useful to detect seasonal clustering. In order to compare the different scan statistic tools the window size will remain the same. Selection of appropriate window size is an important aspect of scan statistics that is discussed later in this chapter.

### 2.5.1 The Binomial Scan Statistic

The classic method for the scan statistic involves counting the number of events in each time interval. The maximum number of events found could be considered a cluster and is called the scan statistic. Using the classical method the probability of a large number of events in a given interval is calculated and a decision can then be made as to whether the cluster is unusual. Neff and Naus [71, 72] published tables of the probability of a cluster. These tables evaluate the cluster up to a total sample size ($N$) of 25.

Wallenstein and Neff [73] further developed the approximation for the distribution of the scan statistic so that large values of $N$, total sample size, could be analysed. Suppose $N$ is the total number of events in an interval of length $T$. Let $r$ denote the ratio of the width $w$ of the window to the total time frame, $T$, $r = \frac{w}{T}$, and set $P(n, N, r) = Pr(m_w \geq n)$ is the probability of getting the maximum value $n$ in any window of width $r$, given that there is $N$ events in total. $Pr(m_w \geq n)$ is the probability under the null hypothesis of finding a value $m$ in a window of width $w$ that is bigger than the cluster $n$.

There are many approximations available for the computation of $P(n; N, r)$. A simple sum of binomial and cumulative binomial probabilities can be utilized [73]. Equation 2.1 shows the Binomial Distribution, $b$, this represents the probability of $n$ successes in a total of $N$ events, where the probability of success is $r$. The window width as a proportion of the total time period is represented by $r$.

$$b(n; N, r) = \binom{N}{n} r^n (1 - r)^{N-n} \tag{2.1}$$

The cumulative sum of probabilities $G_b$ can then be calculated using equation 2.2, where again $n$ represents the number of successes, $N$ is the total number of events and $r$ represents the window width as a proportion of total time.

$$G_b(n; N, r) = \sum_{i=n}^{N} b(i; N, r) \tag{2.2}$$

Using these equations Wallenstein and Neff [73] approximated $P(n; N, r)$ as can be seen in equation 2.5. This approximation of $P(n; N, r)$ is exact for $n > N/2$, $w \leq 0.5$, and gives accurate results in other cases.

$$\begin{aligned} P(n; N, r) &\approx (N - n - 1)b(n - 1; N, r) && (2.3) \\ &\quad -(N - n - 1)b(n; N, r) + 2G_b(m; N, r) && (2.4) \\ P(n; N, r) &= (nr^{-1} - N - 1)b(n; N, r) + 2G_b(m; N, r) && (2.5) \end{aligned}$$

This approximation is easy to implement and a result is relatively easy to obtain using any spreadsheet package such as Excel.

To illustrate this method the Spina Bifida data, described on page 38 will be used. To see if there is evidence of seasonal clustering of Spina Bifida cases a window of 91 days will be used to scan the data. Figure 2.2 illustrates visually the use of a 91 day scanning window. In the diagram the scanning window has been centred on the largest cluster. This cluster occurred in 1998, $27^{th}$ February to $27^{th}$ March. There were nine cases of Spina Bifida in this period; in the two years shown below there was a total of 22 cases of Spina Bifida.


Figure 2.2: Spina Bifida Cases in Ireland, 1997 - 1999, scanned with a 91 day window

Applying the Binomial Scan statistic it is possible to see if a cluster of 9 cases in a 91 day period is significant. In this example total number of events $N = 22$, maximum cluster $n = 9$, window size $r = \frac{91}{730} = 0.125$.

$$\begin{aligned} P(9; 22, 0.125) &= (9 \times 0.125^{-1} - 22 - 1)b(9; 22, 0.125) \\ &\quad +2G_b(9, 22, 0.125) \\ &= 0.0332 \end{aligned}$$

This cluster is significant at $p = 0.033$. This could indicate a tendency for Spina Bifida cases to cluster seasonally.

### 2.5.2 The Scan Statistic on the Circle

Often data can be thought of as circular. Events that occur at around the same time every year could be called cyclical, for example there are many incidents of sunburn in the summer months, not so many in the rest of the year. If one is interested in seasonality then the circle scan statistic should be used. Figure 2.3 shows a pictorial representation of a circular graph, the blue points represent events on a daily basis; in the graph there is a higher density of blue dots in the winter months, so perhaps the graph represents cases of respiratory disease. This higher density begins approximately at the end of November and lasts until approximately mid-February.

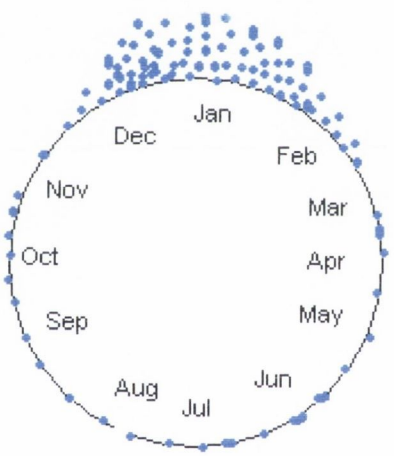


Figure 2.3: A pictorial representation of data on a circle.

A circular scan statistic scans the data on a circle rather than a line, which means that seasonality can be detected. Wallenstein et al. [74] proposed a good approximation to the circular scan statistic. The circular scan statistic, $S_r$, is the

maximum number of events in any arc of length $r$. The probability of $S_r \geq n$ is then evaluated (where $n$ is the number of points in $r$), conditional on the total number of points, $N$, being uniformly distributed on the circle.

Wallenstein, Weinberg and Gould [74] give the following simple approximation for small probabilities:

$$P(S_r \geq n) = P_C(n; N, w) \approx \frac{b(n; N, w)(k - Nw)}{w(1 - w)} \tag{2.6}$$

where $b(n; N, w)$ is calculated as outlined in equation 2.1. As with the Binomial Scan, this method can be applied in Excel. However a loss of precision and accuracy could be expected and a computationally more sophisticated package such as Mathematica will give a higher degree of accuracy.

In order to illustrate the use of the circular scan statistic the Spina Bifida data will be employed once again. To prepare the data for the circular scan statistic, the data for the two years must be pooled for each day. This means simply that the number of Spina Bifida cases on $1^{st}$ January 1998 is added to the number of cases that occurred on $1^{st}$ January 1999, similarly the number that occurred on $2^{nd}$ January 1998 is added to the number of cases that occurred on $2^{nd}$ January 1999, and so on for every day of the year. Once the data have been pooled a scanning window can be selected and the data are scanned. The pooled data and scanning window are plotted in Figure 2.4. In this figure the shaded area represents the scanning window which has been centred on the maximum cluster.

The maximum value found was 14 cases, found between February and June. There was a total of 22 cases of Spina Bifida for the two years. A scanning window of 91 days was used. This cluster was found to be significant as follows,

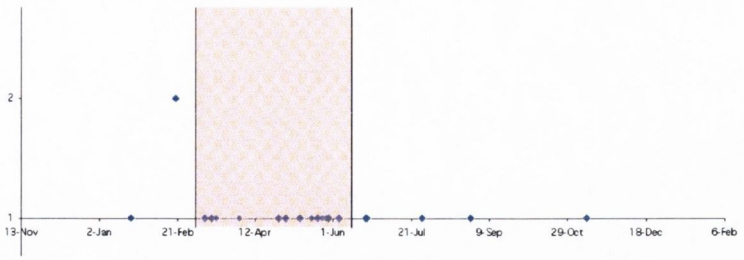


Figure 2.4: Scanning the Spina Bifida data, using a circular scan statistic.

where $n = 14$, $N = 22$ and $w = 0.249$:

$$\begin{aligned} P_C(14; 22, 0.249) &\approx \frac{\binom{22}{14}(0.249)^{22}(0.751)^{8}(14-22\times 0.249)}{0.249(0.751)} \\ &\leq 0.0000 \end{aligned}$$

### 2.5.3 Ratchet Scan Statistic

The previous two versions of the scan statistic are appropriate to use when data are available on a daily level. However in many cases original raw data are not available, but may be available as monthly totals. This can cause problems as the number of days per month varies from 28 to 31. It is still possible to use the scan statistic to detect clustering when data are aggregated to month level. To do this the ratchet scan statistic is used. The ratchet scan statistic is available in a linear form and in a circular form much like the circular scan statistic discussed in section 2.5.2.

#### Circular Ratchet Scan Statistic

Wallenstein et al. [74] proposed the ratchet scan statistic on the circle for large values. Wallenstein, Weinberg and Gould [74] outlined a method for simulating

data to estimate the ratchet scan statistic for large numbers. Let $n_1, n_2, \ldots, n_{12}$ be the number of events in each month of the year and $N$ is the sum of all events ($N = \sum n_i$). $S_i^k$ is the sum of $k$ consecutive months, assuming that $k$ is the chosen scanning window, for example suppose a scanning window of 3 months was used $S_1^k$ is the sum of events occurring in January, February and March, similarly $S_2^k$ is the sum of events in the months February to April. The ratchet scan statistic, $T_k$, is the maximum value of $S_i^k$.

To estimate the asymptotic distribution of the ratchet scan statistic, the method outlined by Wallenstein et al. [74] will be used; the multinormal distribution, with a mean of 0 and variance of 1 is used. The correlation matrices for scan windows of one, two and three months are given below as suggested by Wallenstein et al. [74].

$$Corr(r_i^1, r_j^1) = \begin{cases} \frac{-1}{11} & \forall i \neq j \end{cases} \tag{2.7}$$

$$Corr(r_i^2, r_j^2) = \begin{cases} 0.4 & |i-j| = 1 \text{or} |i-j| = 11 \\ -0.2 & \text{otherwise} \end{cases} \tag{2.8}$$

$$Corr(r_i^3, r_j^3) = \begin{cases} \frac{5}{9} & |i-j| = 1 \text{or} |i-j| = 12 \\ \frac{1}{9} & |i-j| = 2 \text{or} |i-j| = 11 \\ \frac{-1}{3} & \text{otherwise} \end{cases} \tag{2.9}$$

$$\tag{2.10}$$

For a scan window of one month, 200 000 simulations were conducted using the above correlation matrix and a mean value of 1. These simulations re-

sulted in vectors $(Z_1^1, Z_2^1, \ldots, Z_{11}^1)$, $Z_{12}^1$ was estimated using the formula $Z_{12}^1 = -\sum_1^{11} Z_i^1$ . Similarly, for a window of size two months, 200 000 vectors of the form $(Z_1^2, Z_2^2, \ldots, Z_{10}^2)$ were simulated, $Z_{11}^2$ and $Z_{12}^2$ were estimated using $Z_{10+j}^2 = -\sum_{k=0}^4 Z_{2k+j}^2, j = 1, 2$ . Finally, 200 000 vectors of the form $(Z_1^3, Z_2^3, \ldots, Z_9^3)$ were simulated for a scanning window of three months, where $Z_{9+j}^3 = -\sum_{k=0}^2 Z_{3k+j}^3, j = 1, 2, 3$ .

Mathematica [75] was used to implement the simulation. For example, given that 2000 events occur in a year, the number of events that could occur in each month was simulated. For each of six different values of the total sample size, $N$, a multinomial distribution for the twelve months of the year, was simulated 10 000 times. The values of $N$ chosen were 2000, 1000, 500, 250, 100 and 50. These values were selected in order to give a good spectrum of different sample sizes, so that differences between large sample sizes and smaller sample sizes can be ilustrated.

A maximum value for each of the 200,000 multinormal vectors was obtained, the $\alpha^{th}$ percentile of the maximum values corresponded to $R_\alpha^k$, the maximum cluster scan statistic. $T_\alpha^k(N)$, the maximum cluster size, can then be estimated using equation 2.11, as outlined by Wallenstein et al. [74].

$$T_\alpha^k(N) = \frac{Nk}{12} + \sqrt{N} R_\alpha^k \sqrt{\frac{(12-k)(k)}{144}} \tag{2.11}$$

To test the adequacy of the asymptotic distribution, at $\alpha = 0.05$, data were simulated using a multinomial distribution, for $N = 2000$, 1000, 500, 250, 100 and 50. The maximum clusters were then obtained using windows of size $k = 1, 2, 3$ months. The exact $0.05$ critical value was obtained by interpolation of the

two cluster sizes that straddled the critical value. Table 2.1 gives the results of the simulation study.

| | | Asymptotic Theory | | Simulation | | | | |
|---|---|---|---|---|---|---|---|---|
| k | N | $T_k(0.05)$ | $\frac{T_k(0.05)}{N}$ | n | $P(T_k > n)$ | $P(T_k > n+1)$ | $\frac{t}{N}$ | T |
| 1 | 50 | 9.320 | 0.186 | 10 | 0.083 | 0.028 | 0.212 | 10.608 |
| 1 | 100 | 15.621 | 0.156 | 16 | 0.097 | 0.045 | 0.169 | 16.910 |
| 1 | 250 | 32.356 | 0.129 | 33 | 0.076 | 0.042 | 0.135 | 33.770 |
| 1 | 500 | 57.962 | 0.116 | 59 | 0.055 | 0.038 | 0.119 | 59.282 |
| 1 | 1000 | 106.379 | 0.106 | 107 | 0.061 | 0.045 | 0.108 | 107.687 |
| 1 | 2000 | 199.258 | 0.099 | 200 | 0.056 | 0.045 | 0.100 | 200.509 |
| 2 | 50 | 15.215 | 0.304 | 16 | 0.067 | 0.027 | 0.329 | 16.433 |
| 2 | 100 | 26.399 | 0.264 | 27 | 0.077 | 0.039 | 0.277 | 27.712 |
| 2 | 250 | 57.055 | 0.228 | 58 | 0.056 | 0.037 | 0.233 | 58.335 |
| 2 | 500 | 105.096 | 0.210 | 106 | 0.0610 | 0.044 | 0.213 | 106.653 |
| 2 | 1000 | 197.443 | 0.197 | 198 | 0.058 | 0.047 | 0.199 | 198.740 |
| 2 | 2000 | 376.858 | 0.188 | 377 | 0.056 | 0.049 | 0.189 | 377.903 |
| 3 | 50 | 20.432 | 0.409 | 21 | 0.065 | 0.029 | 0.428 | 21.422 |
| 3 | 100 | 36.218 | 0.362 | 37 | 0.056 | 0.030 | 0.372 | 37.223 |
| 3 | 250 | 80.237 | 0.321 | 80 | 0.072 | 0.050 | 0.324 | 80.995 |
| 3 | 500 | 150.084 | 0.300 | 151 | 0.051 | 0.038 | 0.302 | 151.093 |
| 3 | 1000 | 285.475 | 0.286 | 286 | 0.055 | 0.044 | 0.287 | 286.450 |
| 3 | 2000 | 550.169 | 0.275 | 551 | 0.050 | 0.044 | 0.276 | 551.019 |

Table 2.1: Results of asymptotic simulations, compared with simulations for different values of N.

Table 2.1 shows that the value of $T_k$ obtained using asymptotic theory is similar to the value of $T$ estimated using the simulations. However the values do differ by a factor of approximately 1 across all values of $N$. To accommodate this

difference a correction of $+1$ is made to the test statistic. Based on this evidence Wallenstein et al. mapped the ratchet scan onto a statistic whose P-value could be obtained from graphs using the following equation:

$$R^k = \frac{T^k - 1 - Nw_k}{\sqrt{Nw_k(1 - w_k)}} \tag{2.12}$$

where $R^k$ is the test statistic. The corresponding p-values can be obtained using Figures 2.5, 2.6 and 2.7 which were constructed using the simulated data.

The data were smoothed using cubic splines. Figure 2.5 shows the ratchet scan statistic for a window of one month, values of $N \geq 500$ closely approximate the asymptotic distribution, and so the asymptotic distribution curve is used to estimate the $p - value$ in these situations. When $N < 500$ the asymptotic distribution is not as good an estimate, when $N = 50$ the simulated curve provides a better estimate of the p-value than the asymptotic curve.

For a window of size $K = 2$ months, the asymptotic distribution seems to be a good estimate of the p-value for values of $N > 500$. When $N < 500$ the asymptotic distribution is not as good an estimate, when $N = 50$ the simulated curve provides a better estimate of the p-value than the asymptotic curve.

When the window size is 3 months, the asymptotic distribution could be used to read the p-value for all values of $N$; it is especially accurate for $R^3 \geq 2.7$.

**Application of the Circular Ratchet Scan Statistic** To illustrate the ratchet scan statistic the Spina Bifida data will be aggregated to month level. Each of the monthly totals will then be pooled for the two years, as shown in Table 2.2. Once again a three months scanning window will be used. The largest cluster is

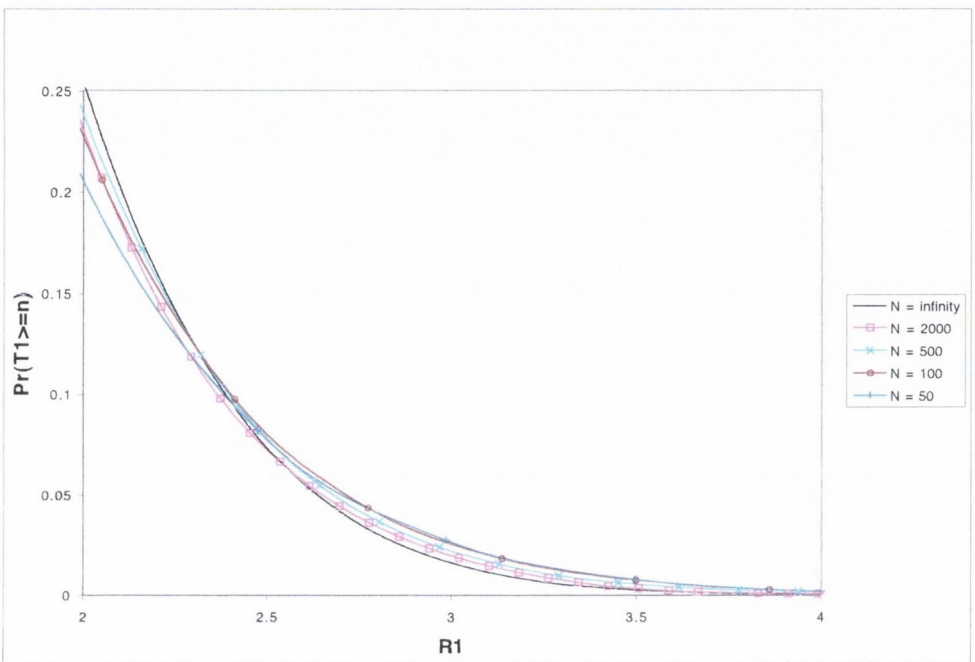


Figure 2.5: Ratchet scan statistic for maximum cluster detection using a window of 1 month.

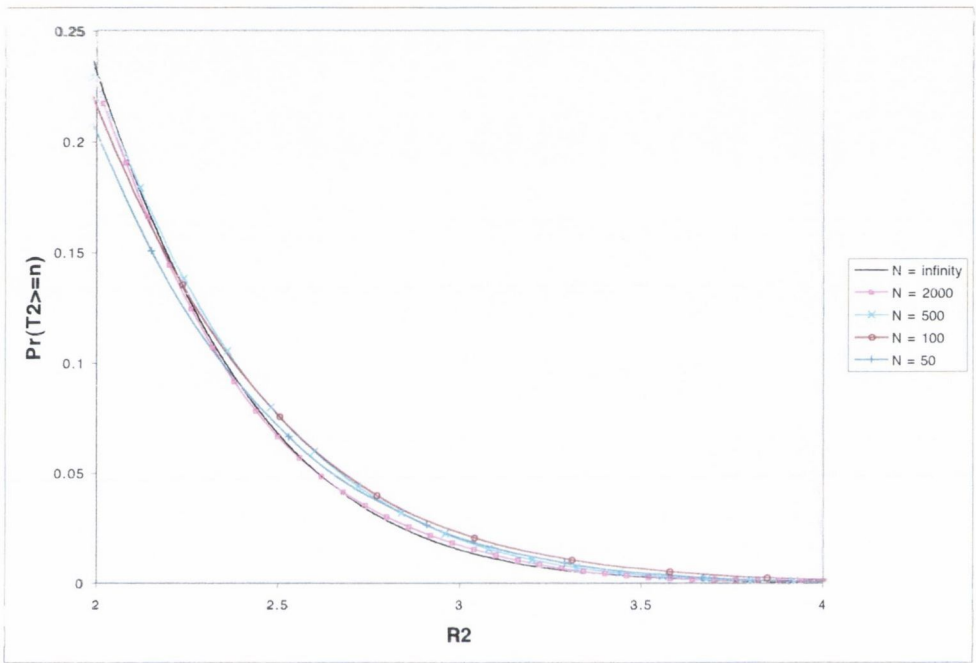


Figure 2.6: Ratchet scan statistic for maximum cluster detection using a window of 2 months.

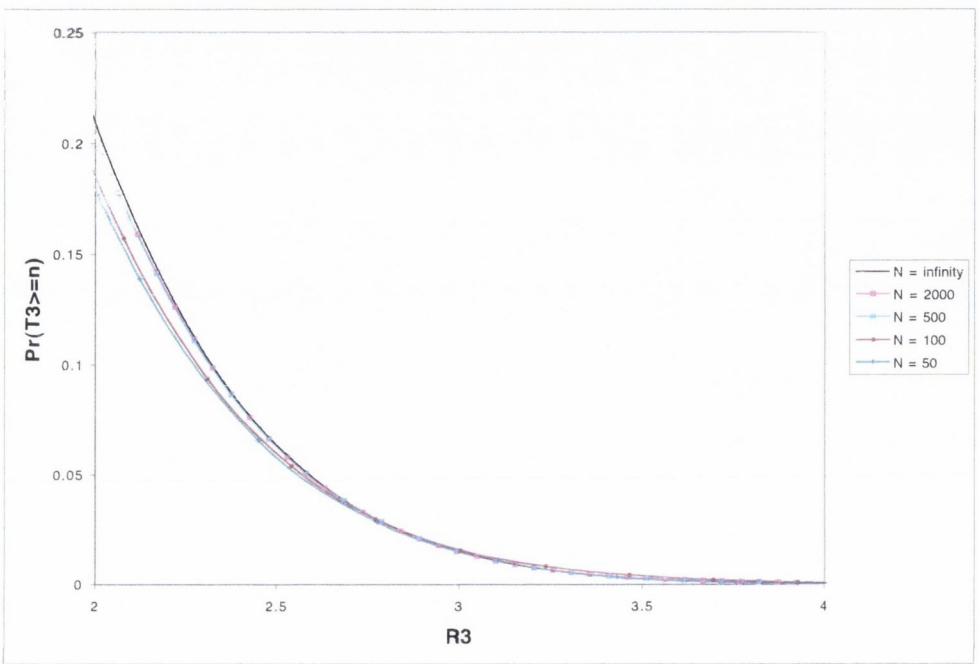


Figure 2.7: Ratchet scan statistic for maximum cluster detection using a window of 3 months.

highlighted in Table 2.2; it consists of 13 cases of Spina Bifida, from March - May.

| Month | 1998 | 1999 | Pooled Spina Bifida Cases |
|---|---|---|---|
| Jan | 1 | 0 | 1 |
| Feb | 1 | 1 | 2 |
| Mar | 3 | 1 | **4** |
| Apr | 2 | 0 | **2** |
| May | 4 | 3 | **7** |
| Jun | 1 | 2 | 3 |
| Jul | 1 | 0 | 1 |
| Aug | 1 | 0 | 1 |
| Sep | 0 | 0 | 0 |
| Oct | 0 | 0 | 0 |
| Nov | 0 | 1 | 1 |
| Dec | 0 | 0 | 0 |

Table 2.2: Spina Bifida data pooled by month.

To evaluate the significance of the cluster, equation 2.12 will be used, where $T_3 = 13$, $N = 22$ and $w = \frac{3}{12}$:

$$R^3 = \frac{13 - 1 - 22 \times 0.25}{\sqrt{22(0.25)(1 - 0.25)}} \tag{2.13}$$

Using Figure 2.7 this figure is significant at approximately 0.0008. With the use of a program in Mathematica the significance was calculated as being between 0.00078 and 0.00084, so the estimate found using the graph is reasonably accurate. Obviously a higher degree of precision can be obtained using Mathematica.

**Linear Ratchet Scan Statistic**

The linear ratchet scan statistic is derived in the same fashion as the circular ratchet scan statistic, outlined in the previous section. The difference between the linear and the circular is that the circular ratchet pools data from a number of years, the linear ratchet does not pool the data, so it is similar to the Binomial scan statistic.

Using Spina Bifida data from 1998 a cluster of nine cases was found with a 3 month scanning window, see Table 2.3. In 1998 there was a total of 14 cases. The test statistic, $R^3$, is found using equation 2.12 as follows:

$$R^3 = \frac{9 - 1 - 14 \times 0.25}{\sqrt{14(0.25)(1 - 0.25)}} = 2.78 \tag{2.14}$$

Figure 2.7 indicates that $R^3 = 2.78$ is significant at approximately 0.035. Using Mathematica the more accurate estimate is between 0.019 and 0.021. The graph and simulated estimate are again sufficiently accurate for the linear scan statistic; even though the Spina Bifida figures are small the asymptotic distribution gives a relatively accurate reading. Once the graphs are available the ratchet scan can be calculated using a calculator. However, as discussed previously the graphs are used for simplicity sake at the expense of precision. Automated computer programs would be more precise, time efficient and easier to use.

### 2.5.4 Poisson Scan Statistic

The versions of the scan statistic that have been looked at so far are all conditional cases, in that the value of $N$ is known and assumed to be fixed. In many cases the total value in a specific time frame may be known and assumed random, thus

| year | Month | Spina Bifida Cases |
|---|---|---|
| 1998 | Jan | 1 |
| 1998 | Feb | 1 |
| 1998 | Mar | **3** |
| 1998 | Apr | **2** |
| 1998 | May | **4** |
| 1998 | Jun | 1 |
| 1998 | Jul | 1 |
| 1998 | Aug | 1 |
| 1998 | Sep | 0 |
| 1998 | Oct | 0 |
| 1998 | Nov | 0 |
| 1998 | Dec | 0 |

Table 2.3: Spina Bifida data aggregated to month for the year 1998.

giving more flexibility. Using the Poisson distribution instead of the Binomial distribution to estimate the probability of a cluster of events will provide a simple model of chance variation in time. The conditional probability of a cluster is denoted by $P(k; N, w)$ and the unconditional probability, based on the Poisson distribution will be denoted by $P^*(k; N, w)$.

There are many approximations for the unconditional probability loosely based on the Poisson process. A number of these will be outlined, as discussed in Glaz et al [54]. Newell [76] and Ikeda [77] derived the asymptotic formula in equation 2.15. This version of the Poisson scan is by far the easiest to implement, and can be calculated with just a calculator, so for a quick approximation it is very useful. This formula is useful for cases were $P^*$ is small as the asymptotic convergence is very slow. In the following equation $\lambda$ is the average number of events

in any unit interval, $k$ is the cluster size, $w$ is the window width and $T$ is the total time.

$$P^*(k; \lambda T, w/T) \approx 1 - exp\{\frac{-\lambda^k w^{k-1} T}{(k-1)!}\} \tag{2.15}$$

Using the Spina Bifida data from 1988 - 1997 the average number of Spina Bifida cases was estimated to be $0.067$ per day. With this information and using equation 2.15 the probability of a cluster of 13 cases in 91 days out of a total of 730 days will be estimated:

$$P^*(13; 48.91, 0.125) \approx 1 - exp\{\frac{0.067^{13}(0.125)^{13-1}730}{(13-1)!}\} \leq 0 \tag{2.16}$$

A more accurate approximation to the scan statistic, using the Poisson distribution was derived by Naus [78]. This approximation can be seen in equation 2.17, While it appears quite complex, this approximation can still be employed, with a small amount of effort, in a package such as Excel.

$$P^*(k; \Psi L, 1/L) \approx 1 - Q_2^*(Q_3^*/Q_2^*)^{L-2} \tag{2.17}$$

where $\Psi = \lambda w$ and $L = T/w$. Also $Q_2^* = Q^*(k; 2\Psi, 1/2)$ and $Q_3^* = Q^*(k; 3\Psi, 1/3)$, the formulas for $Q^*(k; 2\Psi, 1/2)$ and $Q^*(k; 3\Psi, 1/3)$ are respectively:

$$\begin{aligned} Q^*(k; 2\Psi, 1/2) &= (F_p(k-1; \Psi))^2 - (k-1)p(k; \Psi)p(k-2; \Psi) \\ &\quad -(k-1-\Psi)p(k; \Psi)F_p(k-3; \Psi) \\ Q^*(k; 3\Psi, 1/3) &= (F_p(k-1; \Psi))^3 - A_1 + A_2 + A_3 - A_4 \end{aligned}$$

where:

$$
\begin{aligned}
A_1 &= 2p(k;\Psi)F_p(k-1;\Psi)\{(k-1)F_p(k-2;\Psi)-\Psi F_p(k-3;\Psi)\} \\
A_2 &= (0.5p(k;\Psi))^2\{(k-1)(k-2)F_p(k-3;\Psi)-2(k-2)\Psi F_p(k-4;\Psi) \\
&\quad +\Psi^2 F_p(k-4;\Psi)+\Psi^2 F_p(k-5;\Psi)\} \\
A_3 &= \textstyle\sum_{r=1}^{k-1} p(2k-r;\Psi)(F_p(k-1;\Psi))^2 \\
A_4 &= \textstyle\sum_{r=2}^{k-1} p(2k-r;\Psi)p(r;\Psi)\{(r-1)F_p(r-2;\Psi) \\
&\quad -\Psi\textstyle\sum_{r=2}^{k-1} p(2k-r;\Psi)F_p(r-3;\Psi)\}
\end{aligned}
$$

Using the above method in Mathematica the probability of 13 cases of Spina Bifida falling in a 91 day period in any given 2 years is 0.2899, which is not significant.

The result contrasts with that found using the Binomial Scan statistic and the ratchet scan statistic.

## 2.6 Computational Requirements

In the versions of the scan statistic that were outlined in this chapter it is possible to implement an approximation of each type in Excel, and in some cases a calculator will suffice. However, for optimal results, more accurate, powerful computing methods are required. For each of the Binomial Scan, Ratchet Scan, Circular Scan and the Poisson Scan there are Mathematica [75] programs available. If Mathematica is available then using these programs would be preferable and less time consuming than implementing the scan statistic in a package such as Excel. There are also a number of websites which do certain scan statistic calculations,

Kulldorf's Satscan [79] being one of the more well known sites.

## 2.7 What Window Size?

In the examples studied in this chapter a three month scanning window was used in all situations. However as there is no preset window size, any size window could have been used. The size of window should be chosen based on the data or type of situation that is to be monitored: a window too small may not be capable of detecting clusters in some cases, and in other cases windows may be too big and there may be multiple clusters inside a scanning window - again making the detection of a single cluster impossible.

There are cases where very small windows are required. Hryhorczuk et al. [61] used a window of 3 days when they implemented the scan statistic to detect clustering of carbon monoxide poisoning. This is because carbon monoxide outbreaks are typically acute and usually limited to one or a few days.

Evidence suggests that copycat suicides usually take place within 70 days of the initial event. Therefore if scanning for copy-cat suicides a window of at least 70 days would be used in order to detect clustering of this type of suicide.

The window size to be used for detection of clusters is totally based on the situation being studied. In the above examples the events dictated the window size, carbon monoxide poisoning happens within 2-3 days so a window size any larger would be futile and would possibly only detect multiple clusters of carbon monoxide outbreaks, hence the detection of single outbreaks would become impossible as each outbreak would become blurred with other outbreaks occurring within the window.

In general it would be prudent to investigate the data and situation thoroughly to determine if an appropriate window size is suggested by data. Thus in the carbon monoxide example, determining window size would require investigation of the length of carbon monoxide clusters, ie. deciding on the time frame within which a carbon monoxide cluster occurs, and then setting the window size to an informed 2 or 3 days.

It is more likely that no optimum window size is known from the data. In this situation it can be a case of 'best educated guess' window size. This would mean not choosing a very short window size for a rare event, or a long window for something that occurs rather frequently. To help inform the decision making it is important to examine the frequency of events in the population of interest and basing the window size on the frequency.

A good base would be to set the window size as 3 months, as this is a nice proportion of a year. Then examine the frequency of events, if there is likely to be a large number of events occurring in a three month period (200+) then perhaps a smaller window should be used, if there is only a small frequency in that window size ($\leq 2$) then perhaps a larger window should be used.

There will also be situations when the window size is dictated by the research question being asked. For example suppose it is of interest to detect if a particular event is seasonal, in this case it does not matter what the frequency of events is, seasonality is the determining factor and so a window size of 3 months should be used. In other situations it might be of interest to detect clustering of events at weekends - use a 2 day window, or clustering over a 1 year period - use a 1 year window.

It is possible to apply a variable window width; in this way a fixed window

width does not have to be specified. One issue with this method is the problem of multiple testing. However this can be catered for by using the appropriate statistic to account for the multiple testing or by Monte Carlo simulation.

## 2.8 Conclusion

The scan statistic appears to be a viable resource to monitor health impacts. There are a number of versions so if the data are continuous and $N$ (the total sample size) known and assumed to be fixed, the Binomial Scan statistic can be used. If $N$ is known but assumed to be random then the Poisson Scan statistic can be used. When looking at seasonal events the circular scan statistic is ideal. Aggregated data can be manipulated using the ratchet versions of the scan statistic.

While many different data types are dealt with using the different versions of the scan statistic, the scan statistic is relatively easy to implement. For each of the versions it is possible to get an approximation using a spreadsheet package such as Excel. For optimal results a computationally more powerful and more accurate option would be Mathematica.

In the following chapters the versions of the scan statistic discussed here will be applied in very different situations. The applications of the scan statistic will illustrate its use in real, applied situations and any problems can be highlighted and alternatives suggested.

# Chapter 3

# Negative Health Impacts

One of the most important aspects of health impact assessment is to alert to a possible negative impact that a proposed policy may have on the health of the population. While the role of HIAs is to minimise negative health impacts resulting from a new policy, sometimes the unforeseen can happen. There are many industries and technologies such as mobile phone masts, pharmaceutical industries, genetically modified crops, and, as yet, there is little evidence of the health impacts that such industries may have in the long term.

There are some instances where there is public uneasiness regarding a new policy - for example, siting a proposed incinerator, and, although emissions from incinerators have been reduced and the level of dioxins emitted is now thought to be minimal, there is still debate and a lack of evidence on the long term health impacts of even low levels of dioxins. In this situation the public should be reassured that health effects will be closely monitored and any negative effects will mean that a thorough investigation and enquiry will be launched.

A new transport system might be expected to perhaps increase the health of

city's inhabitants. People will no longer have to sit in traffic jams in their cars, they may get to work faster and this will lead to a stress-free life as they get to spend more time with their families. However, a new transport system may increase accidents and introduce new varieties of accidents and thus increase the frequency and severity of injuries.

By monitoring for certain health events, unforeseen health impacts can be addressed in a timely manner and measures put in place to correct the occurrence of these health events. In the case of suicide, there may be copycat suicides [1] or suicide contagions [2] spread through the press. It is not possible or ethical to carry out a health impact assessment of the impact of a media report of a suicide, and whether this media coverage will lead to further suicides. However, perhaps, if suicides were constantly monitored then a retrospective health impact might be observed and the necessary health services and provisions put in place.

This chapter will look at monitoring suicides, tram incidents, and cancer cases near an incinerator. There is an incinerator proposed for Ringaskiddy, Co. Cork. Monitoring techniques that could be used to monitor cancer cases in Ringaskiddy will be examined. A new tram started in Dublin in July 2004, with a second line due to begin October 2004. The feasibility of the monitoring of tram related incidents will be discussed and illustrated. For each of the examples in this chapter, the framework of health impact assessment will be applied, as outlined in section 1.2.3, page 5.

[1] The term copycat refers to the tendency of humans to duplicate the behaviour of others. Copycat suicides are defined as duplications or copies of a suicide due to repeated accounts or depictions of the initial suicide in the media. [80]

[2] A suicide contagion refers to the tendency of one or more person's suicidal behaviour to influence another person to attempt or complete suicide. [81]

## 3.1 Monitoring Suicide in Ireland

The scan statistic is beneficial for other public health situations. While monitoring events in a HIA is important there is also a need for public health monitoring in many areas. The monitoring of suicide will be examined and the use of the scan statistic as a public health monitoring tool illustrated. While this is not specifically a 'HIA' example, it is a useful example of using the scan statistic as a monitoring tool.

Suicide is defined by the Centre for Suicide Prevention [82] as "intentional, self-inflicted death". Experts in the field suggest that a suicidal person is feeling so much pain that they can see no other option. They feel that they are a burden to others, and in desperation see death as a way to escape their overwhelming pain and anguish. The suicidal state of mind has been described as constricted, filled with a sense of self-hatred, rejection, and hopelessness. The following were found to be the most common predictors of suicide [83]:

- Previous suicide attempt
- Mental health - particularly mood disorders such as depression
- Combined mental health and substance abuse issues
- Family history of suicide
- Hopelessness/Helplessness
- Impulsive and/or aggressive tendencies
- Barriers to accessing mental health services

- Loss (relationships, health, identity status)
- Stressful Life event
- Accessibility to lethal methods, especially guns
- Unwillingness to seek help because of stigma attached to mental health issues and suicidal thoughts
- Exposure to suicide (family, peers, significant others)
- Physical, emotional and sexual abuse
- Legal issues/arrests/incarceration
- Sexual identity conflict

One of the indicators or predictors for suicide is exposure to suicide, so the suicide of family members, peers or significant others is a negative health impact. There are reports, that in the wake of the suicide of Kurt Cobain, approximately 60 - 80 of his fans around the world also committed suicide [84].

There is no monitoring of suicides in Ireland, a systematic monitoring system could alert to a sudden increase in the number of suicides and perhaps more preventive strategies put in place to reduce the numbers of suicides. If there is evidence of clustering of suicide it could be indicative of copycat suicides or seasonal suicides.

A known predictor of suicide is exposure to suicide, so media reporting or knowledge of a suicide may lead to further suicides. Other health impacts of suicide could be the impact a suicide may have on family and friends of the victim. The analysis of the impact of suicide on family members is beyond the scope

of this thesis. For this illustrative example only clustering of suicides will be considered.

### 3.1.1 What is the background to suicide in Ireland?

In 2001 a National Study on Suicide in Ireland was completed. It was published by the Departments of Public Health on behalf of the Chief Executive Officers of the Health Boards. Information was gathered on all suicides that occurred in Ireland in 1997, and for some regions of Ireland the study was extended to 1998.

The study found high rates of suicide among males, who were found to be five times more likely to commit suicide than females. Young males under the age of 30 years were found to be particularly at risk. Mental health disorders and depression were found to be the highest risk factors for any suicide: many of the victims had visited general practitioners with complaints relating to psychological symptoms prior to committing suicide.

Unemployment was found to be a high risk factor for suicide, as well as significant life events such as relationship problems. Misuse of alcohol prior to committing suicide was a common trait among victims. It should be remembered that suicide is more prevalent among young people in the population who perhaps are more likely to misuse alcohol.

Data from the period 1995-1996 will be used to investigate clustering of suicides. The data used was mortality data obtained from the Central Statistics Office in Ireland. In that period a total of 810 individuals throughout the Republic of Ireland took their own lives. Over 35% of these were under 30 years of age, 80% were male.

**Is there evidence of a clustering of suicides in Ireland?** A clustering of suicides could be an indicator of an impact on health. For example a closure of a number of industrial plants could lead to unemployment and depression which are risk factors for suicide. Clustering of suicides could be indicative of copycat suicides; media coverage of suicides, as well as community coping mechanisms, would then need to be reviewed.

To investigate clustering of suicide in Ireland a window of size 91 days, equating to approximately three months, was used. A window of this size will detect any seasonal clustering of suicide. The largest number of suicides in a 91 day period during the years 1995-1996 was 135. This cluster occurred between the $5^{th}$ June 1996 and the $3^{rd}$ September 1996.

The Binomial Scan statistic, as outlined in section 2.5.1 was used to examine if this cluster was significant. The Binomial scan statistic was chosen in this instance as it accommodates retrospective situations appropriately; we know the total number of suicides in the two year period and can assume that this total is fixed. Applying the Binomial Scan statistic (equation 2.5 page 39 it was found that the cluster of 135 cases of suicide was significant.

$$\begin{aligned} P(135; 810, 0.124) &= (135 \times 0.124^{-1} - 810 - 1)b(135; 810, 0.124) \\ &\quad +2G_b(153, 810, 0.124) \\ P(135; 810, 0.124) &= 0.0247 \end{aligned}$$

The above cluster incorporated the entire population. The population will now be examined stratified by sex and age to investigate if there are certain groups in the population that cluster significantly.

The data were split into the following age groups: $< 20$, 20-29, 30-39, 40-49, 50-64 and 65 years and over. These age groups were selected as it was felt that they represented the different cycles in an individual's life. The data were also stratified by sex.

The window size was again selected to be 91 days for consistency in the analysis. Tables 3.1 and 3.2 show for males and females the maximum cluster size, total number of suicides and probability for each age stratum. There was only one significant cluster, males aged 20-29 had a significant cluster of suicides from $31^{st}$ May 1996 to $30^{th}$ August 1996.

| Age group | Cluster Size | Total Size | % | Probability |
|---|---|---|---|---|
| <20 | 15 | 63 | 23.81 | $> 0.1000$ |
| 20-29 | 44 | 189 | 23.28 | 0.0026 |
| 30-39 | 26 | 143 | 18.18 | $> 0.1000$ |
| 40-49 | 21 | 115 | 18.26 | $> 0.1000$ |
| 50-64 | 16 | 87 | 18.39 | $> 0.1000$ |
| 65+ | 14 | 67 | 20.90 | $> 0.1000$ |

Table 3.1: Clustering of suicides among males in different age groups.

| Age group | Cluster Size | Total Size | % | Probability |
|---|---|---|---|---|
| $< 20$ | 4 | 16 | 25.00 | $> 0.1000$ |
| 20-29 | 9 | 28 | 32.14 | $> 0.1000$ |
| 30-39 | 8 | 32 | 25.00 | $> 0.1000$ |
| 40-49 | 8 | 30 | 26.67 | $> 0.1000$ |
| 50-64 | 7 | 31 | 22.58 | $> 0.1000$ |
| 65+ | 3 | 9 | 33.33 | $> 0.1000$ |

Table 3.2: Clustering of suicides among females in different age groups.

**Is there evidence of seasonal clustering of suicides?** Seasonal clustering of suicides has been found in many countries. If seasonal clustering of suicides is apparent, additional mental health resources could be initiated in seasons where higher suicide rates were expected. Evidence of seasonal clustering would be helpful in describing the clustering of suicides revealed by section 3.1.1.

In order to investigate seasonal clustering the ratchet scan statistic in section 2.5.3 or the circular scan statistic in section 2.5.2 could be used. Data on a daily basis are available, so the circular scan statistic will be used. The number of suicides that happened on each day in 1995 and 1996 were pooled; the number of suicides occurring on the $1^{st}$ January 1995 was added to the count for the $1^{st}$ January 1996 and so forth. The year 1996 is a leap year, so data for the $29^{th}$ of February was omitted for this calculation.

As seasonality is usually considered in terms of a three month period a window size of 91 days was used to find the maximum cluster. The maximum number of suicides occurring in any 91 day period was 235, out of a possible 810. Using equation 2.6 this cluster proved to be non-significant. There is no evidence of seasonality of suicides among the population of Ireland in the years 1995-1996.

In order to test if there was seasonality among a particular group the data were divided into the same age and sex strata as before. Tables 3.3 and 3.1.1 show the results, the only group to be significant at a 10% significance level were males aged 20-29 years, this is the same group that had a significant cluster using the non-seasonal method. However, when using the binomial scan method a 91 day window was used which would equate to a three month or seasonal scanning window.

| Age group | Cluster Size | Total Size | Probability |
|---|---|---|---|
| <20 | 24 | 63 | >0.1000 |
| 20-29 | 66 | 189 | 0.0572 |
| 30-39 | 45 | 142 | >0.1000 |
| 40-49 | 39 | 113 | >0.1000 |
| 50-64 | 30 | 86 | >0.1000 |
| 65+ | 21 | 66 | >0.1000 |

Table 3.3: Seasonal clustering of suicides among males in different age groups.

| Age group | Cluster Size | Total Size | Probability |
|---|---|---|---|
| <20 | 7 | 16 | >0.1000 |
| 20-29 | 11 | 28 | >0.1000 |
| 30-39 | 14 | 32 | >0.1000 |
| 40-49 | 12 | 30 | >0.1000 |
| 50-64 | 12 | 31 | >0.1000 |
| 65+ | 4 | 9 | >0.1000 |

Table 3.4: Seasonal clustering of suicides among females in different age groups.

**Is there evidence of copycat suicides?** There has been much discussion on media coverage of suicide and how it can lead to contagion or copycat suicides. Increases in suicides rate following media coverage of a suicide have been described in both Britain and the USA [85, 86]. It is reported [87] in Britain that following a widely publicised political suicide, a woman burnt herself to death, and there was an excess of 60 suicides by burning in the following 12 months.

Past research tends to indicate that copycat suicide means that the same method of termination is used or copied by a number of different individuals in a short period of time. The effects of copycat suicides could be witnessed for a period of up to 70 days after the initial event [88].

In order to investigate copycat clustering the method used to commit suicide would need to be known. The type of suicide is available in the form of ICD codes. The ICD code to identify poisoning by solids or motor vehicle exhaust fumes are respectively E950 and E952, the ICD code for suicide by cutting is E956, for jumping it is E957, drowning is E954, for suicide by firearms the ICD code is E955 and the ICD code is E953 for suicide by hanging or strangulation. As suicide is a rare event, when cases are subdivided by group it gives fewer cases so it can be difficult to detect clustering.

To investigate if there is any evidence of copycat suicides in Ireland, clustering of different methods of suicide was examined, and the data were scanned using a window of 70 days. Table 3.5 shows the methods used to commit suicide. Hanging was the most frequent method used to commit suicide, followed by drowning and poisoning.

Using the Binomial scan statistic clustering of hanging was significant; all ages, sexes and areas were included in this cluster. When the data were stratified

| Method | Cluster | Total | p-value |
|---|---|---|---|
| Cutting | 4 | 8 | >0.1000 |
| Drowning | 28 | 195 | >0.1000 |
| Jumping from high place | 4 | 18 | >0.1000 |
| Poisoning by other gas - car fumes | 12 | 65 | >0.1000 |
| Poisoning by solids or liquids | 17 | 100 | >0.1000 |
| Firearms and Explosives | 13 | 71 | >0.1000 |
| Hanging, Strangulation, Suffocation | 57 | 330 | $< 0.05$ |

Table 3.5: Copycat suicides.

by age and sex no clustering was observed. However, by stratifying the data by sex, age and method of suicide, the values of $N$ become small and this leads to a power problem as discussed in section 5.3 on page 125, so that in order for a cluster to be detected as a significant cluster it needs to represent a large proportion of the total sample.

A suicide contagion is the exposure of suicide in one's family, network or through media groups, which leads to thoughts of suicide of suicidal behaviours. Exposure to suicide is a risk factor for suicide, and so suicide clusters occur, especially among young adults. A contagion may not necessarily be a copycat suicide, hence the analysis of clustering of suicides in section 3.1.1 could indicate that there is evidence of contagion suicide among males aged 20-29, while the cluster of suicides by hanging could be considered a cluster of copycat suicides.

### 3.1.2 Decision Analysis—Who is most at risk?

Males aged 20-29 seem to be most at risk of suicide by exposure to suicide through media, family or peers. This is the only group that showed significant clustering.

Males aged 20-29 will be used to illustrate a monitoring method that could be used to monitor suicides.

### 3.1.3 Monitoring & Evaluation

In order to monitor suicides the Poisson scan statistic will be used. Using data from 1992-1994 for males aged 20-29, the average number of suicides per day was found to be 0.22. Using this value the Poisson scan statistic can be used to set up a monitoring chart.

A window of 91 days will be used as seasonal clustering was found to be significant. Using the Poisson Scan statistic, as outlined in section 2.5.4, thirty suicides among males aged 20-29 would not be significant (p=0.34). Any cluster greater than 35 suicides would be a significant cluster (p = 0.04). Using the value of 35 a monitoring chart can be set up–as in Figure 3.1–any cluster over 35 in this graph is significant. In August 1996 there is an out of control value which indicates a significant cluster which could be indicative of copycat suicides, suicide contagion or of some other social reason such as the closure of a large company and a downturn in the economy.

### 3.1.4 Conclusion

There is evidence of clustering of suicides in Ireland. There has been no published evidence of copycat suicides in Ireland. The analysis conducted here suggests that there is evidence of copycat suicides, and further work is needed to investigate this cluster. The Poisson scan statistic proved to be an effective monitoring tool for suicides.

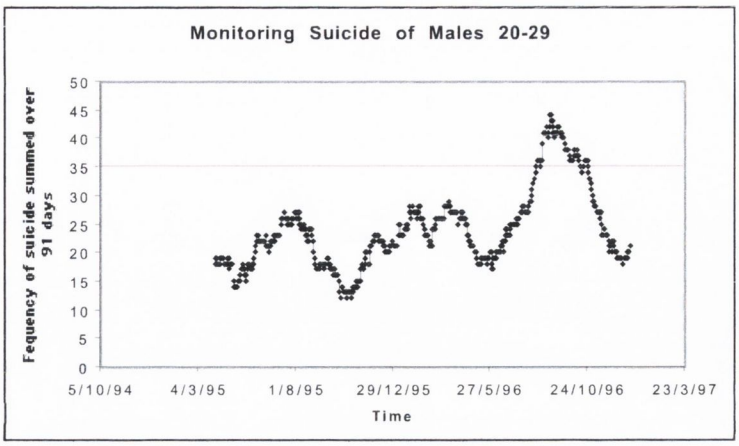


Figure 3.1: Monitoring suicide of males 20-29.

However, it should be remembered that this is only an initial enquiry and only suggests some evidence of possible copy cat suicides. Further work would need to uncover whether there was a highly publicised suicide that resulted in the copycat cluster. The evidence produced here is not enough to suggest a definite copycat suicide cluster, each case in the cluster would need to be investigated, it could be that hanging is a somewhat more 'accessible' method of committing suicide. However, the scan statistic does give enough evidence to suggest further study.

## 3.2 Health Impact Assessment of an Incinerator in Ringaskiddy

### 3.2.1 Screening

An incinerator could have an impact on public health so a HIA is imperative. As the proposed incinerator in Ringaskiddy is so controversial, a HIA may help to ease concerns of worried locals.

### 3.2.2 Scoping

Incinerators have caused controversy wherever they have been proposed. There is no agreement on the extent of the risks attributable to incinerators and it is this that worries residents living in the shadow of incinerators.

Incinerators have been known to cause soft tissue sarcomas [89], adverse respiratory effects [90], low sex ratio births [91] and congenital anomalies such as Spina Bifida and heart defects [92]. However, all of these studies have involved old incinerators and incinerators within very industrial zones. There is no evidence of a health risk to residents near modern incinerators with low levels of dioxin emissions. As there is no evidence of a risk near modern incinerators this is essentially an illustraive example of using the scan statistic as a monitoring tool in HIA. It should be remembered that even though there is no evidence of a risk from modern incinerators it does that mean that there is absolutely no risk.

The incinerator in Ringaskiddy is not as yet operational, so essentially this is a prospective health impact assessment. As the evidence of health risks posed by incinerators is somewhat contradictory it is vital that monitoring of the vari-

ous suspected health occurrences in the proximity of incinerators are monitored. To illustrate a monitoring system for this situation lung cancer will be chosen because it has been shown that it is a risk factor for inhabitants near older incinerators [90], the Poisson scan statistic will be used to set up the monitoring system. To implement the Poisson scan statistic the expected incidence of lung cancer in Ringaskiddy at present is required; the incidence of lung cancer in Ireland will be used to derive the Ringaskiddy incidence.

### 3.2.3 Appraisal

#### Ringaskiddy Area and Population

Ringaskiddy is situated on Cork Harbour, Co. Cork, approximately 13 kilometres from Cork city, as the crow flies, or 18.7 kilometres by road. Ringaskiddy was formerly a fishing village but since the building of a ferry terminal has become an important industrial centre. It has attracted high profile pharmaceutical industries such as Pfizer Pharmaceuticals as well as some chemical industries such as Chemical Carbon Group Ltd., among a list of other manufacturing companies. Approximately 1200 people live in the vicinity of Ringaskiddy and the proposed incinerator.

#### Proposal for Ringaskiddy

Indaver Ltd. is proposing to build an integrated waste management facility [93] in Ringaskiddy. According to their plans, which are publicly available on their website and in hard copies direct from the company, it will include a recycling park, a waste transfer station and a waste-to-energy plant. The recycling park is

an area where the community can bring their recyclable household waste. The waste transfer station is a place where industrial hazardous and non-hazardous waste can be sorted and repacked where necessary, and material not suitable for incineration on site sent to appropriate sites elsewhere.

The waste-to-energy or incineration plant is causing controversy locally and nationally. The proposal will mean burning waste at high temperatures, in a controlled environment, using the heat to generate electricity. This will reduce the waste to an ash which will be approximately one tenth of the original volume of waste, and one quarter of its original weight.

The waste that they propose to incinerate, initially in phase 1, consists of hazardous and non-hazardous waste. Hazardous waste will include solvents produced by pharmaceutical and chemical plants. Non-hazardous waste from local industry such as shops, factories, agriculture, hotels and restaurants will be handled in the plant.

Incineration of waste produces dioxins, which are harmful substances, even in small quantities. The proposed incinerator for Ringaskiddy will incorporate a two stage dioxin removal system. This should ensure that dioxins are reduced to a level below the limit set by European Union legislation.

According to the Environmental Protection Agency's (EPA) figures, Ireland produced 220,000 tonnes of reported industrial hazardous waste in 1998, and 62% of this total was produced in County Cork. The amount of hazardous waste exported for incineration in 1999 was 61,266 tonnes. The EPA's National Hazardous Waste Management Plan states that the quantity of hazardous waste exported for incineration justifies the construction of a thermal treatment facility for hazardous waste in Ireland. The Ringaskiddy facility will eliminate the need to export the

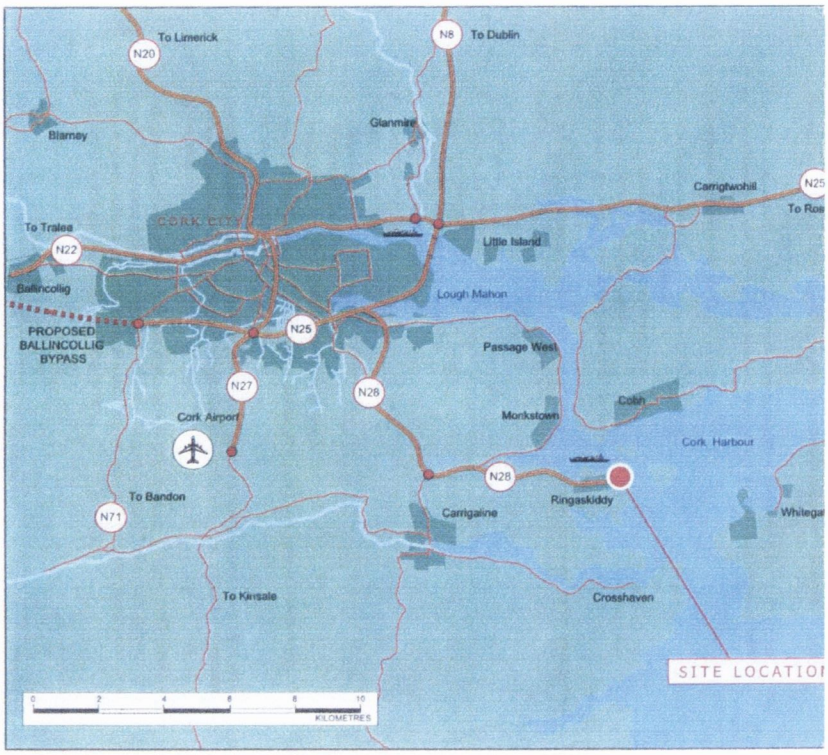


Figure 3.2: Proposed site of the Ringaskiddy incinerator.

majority of industrial hazardous waste, such as solvents, for incineration.

The proposed site for the Ringaskiddy waste management facility is identified in Figure 3.2 [93]. It will be located in the north-eastern corner of the Ringaskiddy peninsula. The site will occupy an area of approximately 12 hectares. The road from Ringaskiddy village will form the northern boundary, cliffs along the shore will form the eastern boundary and on southern and western boundaries there is agricultural land.

### 3.2.4 Decision Analysis

There is no evidence to suggest that the incinerator will be harmful to the residents of Ringaskiddy, as the incinerator is to be located downwind from the town, and with constant monitoring of dioxin emissions, the health risk is presumed to be minimal. However as the long-term effect of exposure to minute amounts of dioxin is unknown, the health of the inhabitants of the town should be monitored.

Another possible health risk for the residents of the town will be the increased traffic. There will be a substantial increase in the number of trucks which will cause air pollution, noise pollution as well as extra traffic and it's associated risks. Many of these trucks will also be transporting toxic waste which could pose another health risk. As data for these health risks is difficult to obtain, for the purposes of this illustrative example incidence of cancer will be monitored as a possible health effect of the dioxin emissions.

### 3.2.5 Monitoring & Evaluation

The incidence of mortality from lung cancer in Cork was 32.69 per 100,000 in the year 1999. In Ringaskiddy the incidence would be expected to be 0.39 occurrences per year. This means that every 10 years four people would be expected to die from lung cancer in Ringaskiddy, under normal conditions. Similarly, 2 cases of Non-Hodgkin's Lymphoma could be expected every 100 years, and 5 cases of soft tissue sarcomas could be expected every 100 years.

Given that the current incidence of lung cancer in Ringaskiddy can be estimated, as has been done, a monitoring chart could be set up using the Poisson scan statistic as in section 3.1.3. In order to illustrate the monitoring tool in the

context of the incinerator example simulated data will need to be employed. As the rate of lung cancer in the vicinity of the incinerator could be expected to increase, the non-homogenous Poisson process (NHPP) will be used to simulate the data. NHPP allows for a change in rate over time, an alogrithm used to simulate the NHPP is given in the Appendix, page 148.

To simulate the data correctly an estimate of the expected increase in lung cancer incidence is required. Biggeri et al. [94] found an excess of lung cancer cases, with a relative risk of 6.7, close to the source of an incinerator. This relative risk did derive from a study in a highly industrial zone with many exposures so the figure will only be used to illustrate this example of a monitoring chart. Using this relative risk a possible scenario can be illustrated. Using this value of relative risk, the mortality due to lung cancer was simulated using a NHPP for 20 years after the proposed initial operation of the incinerator on $1^{st}$ January 2007.

As lung cancer cases are not frequent, a slightly longer window than has been used, so far in this thesis, will be employed. A window of half a year or 183 days will be used to scan the data. In Ringaskiddy 0.1958 mortalities due to lung cancer should occur in this period. Using the Poisson Scan statistic as outlined in Chapter 2, section 2.5.4, a critical value of three deaths in lung cancer per 183 days could be used, as the Poisson scan statistic found that three cases of lung cancer in a 6 month period was significant.

Figure 3.3 shows the simulated data, summed over 183 days. The first out of control pointed is noted at September 2008, this is approximately 1.5 years post operation of the plant, so using a window of this size and the Poisson scan statistic an increase in cancer cases is highlighted quickly.

The window size for this example was selected rather arbitrarily. If a window

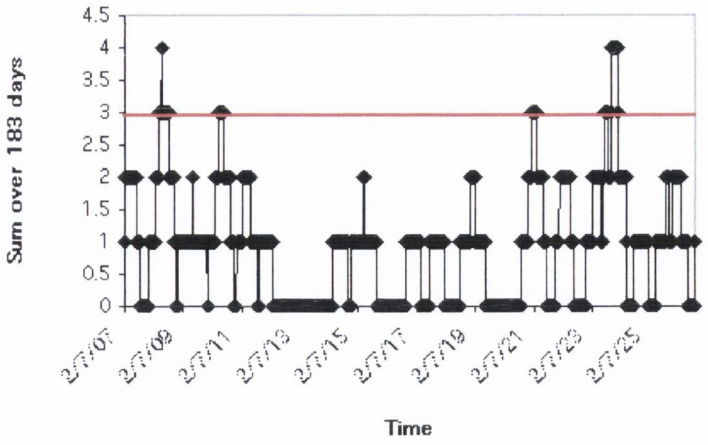


Figure 3.3: Monitoring of simulated lung cancer cases using a 183 day window.

size of 365 days were used (as in Figure 3.4), the critical value would remain at 3, and the first alert would be at the start of October 2008, approximately the same time as the 183 day window.

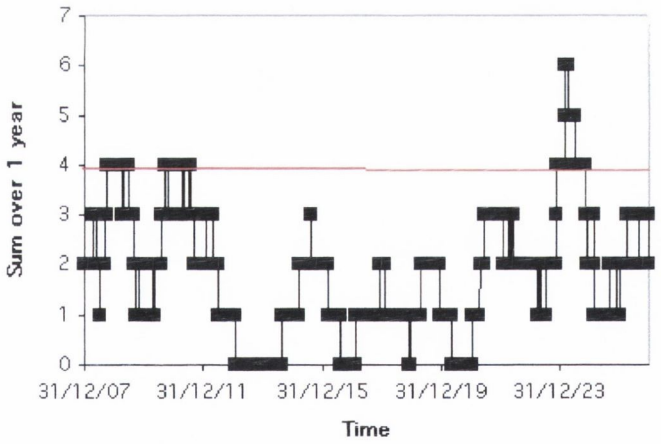


Figure 3.4: Monitoring of simulated lung cancer cases using a 365 day window.

If the incinerator does cause an increase in lung cancer then the increase will be spotted quickly using the scan statistic as a monitoring tool. The monitoring method used above is efficient. It should be remembered that the simulation used here assumes that the proposed incinerator in Ringaskiddy will increase the incidence of lung cancer by a relative risk of 6.7, and it also assumes that the increased risk will occur immediately. It is quite likely that if there is an effect it will be a cumulative effect and any impact will not be observed for many years. However, if the monitoring system is in place, any impact will be observed in a timely manner.

## 3.3 Health Impact Assessment of a Tram System

A tram system, LUAS, began operation in Dublin on the $1^{st}$ July 2004, with a second tram line going into operation in October 2004. There is little data available on the incidence of accidents or incidents involving the LUAS trams. However, there have been a number of media reports of minor collisions.

There is no exact data available on the LUAS incidents, to illustrate how a tram-incident monitoring chart could be useful a tramline in Houston, Texas will be used. Data are available on the various accidents and incidents involving the tram since it began operation in January 2004. This tram will be investigated if it is possible to monitor tram accidents and if there are any benefits from doing so.

### 3.3.1 Screening

A health impact assessment has been carried out on a tramline in Merseyside [95]. However as tramlines vary considerably this HIA could not be used as a basis for a HIA on another tramline. The Merseyside tram has not yet been built or begun operation so no monitoring of health has taken place.

It is difficult to compare light rail systems, as they tend to vary enormously according to their length and configuration. For example some tramlines are separated from road traffic, while in other cities trams and cars share the same lanes. To get an expected accident rate for the tramline in Houston, a similar tramline in Sacramento will be used. The tramline in Sacramento has the same length of on-road track as Houston so it does serve as a somewhat useful example of what may be expected in terms of accident rate in Houston.

### 3.3.2 Scoping

A new tram system will improve the public transportation in a city and therefore improve access to facilities such as schools, universities and hospitals. These will obviously all have positive impacts on health. However a tram system can also be at the centre of accidents and injuries for passengers, pedestrians and other road users.

A study undertaken in Gothenburg [96] found that tram injuries were an important cause of traffic injuries and fatalities among passengers. Most tram injuries were found to have occurred at or near a tram stop, so it could be possible to employ extra safety measures at these high risk locations.

### 3.3.3 Appraisal

Sacramento has on average 4 accidents per 7.5 miles of tram line every year according to the National Transportation Database [97]. This average could be used in order to monitor the number of accidents on the Houston Metro. The Houston tram line is approximately 7.5 miles long, so 4 accidents could be expected in a one year period, according to the Sacramento figure. Using the Poisson scan statistic, with a window size of a month, a significant cluster is four tram accidents in 1 month.

### 3.3.4 Decision Analysis

The new tram system should go ahead, with monitoring of incidents. If there are more incidents than expected then a thorough investigation of safety should be initiated.

### 3.3.5 Monitoring and Evaluation

A cluster of tram incidents are indicative that the necessary safety measures are not in place. Initially a small scanning window should be used to catch a cluster. A window size of 30 days will be used in this case. The data were obtained from the Action America [98] website with the permission of the site owner. It indicates that within the first month, a significant cluster was observed. Figure 3.5 shows that while there are many significant clusters, there are periods when the number of accidents in a 30 day period drops. In the last month of monitoring (August) there have been no significant clusters, which could be indicative of a solving of teething problems.

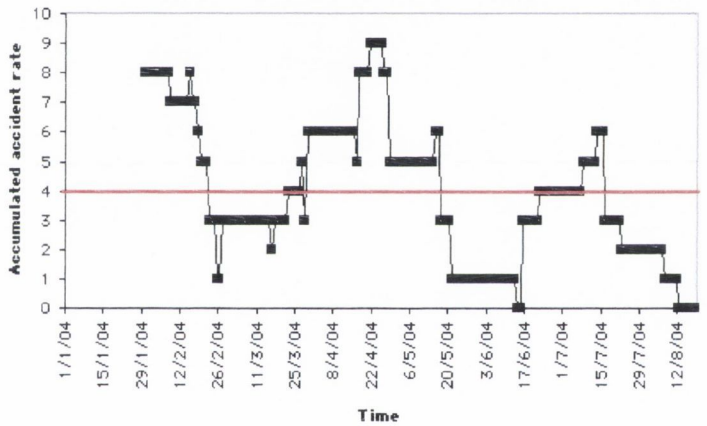


Figure 3.5: Monitoring of tram incidents.

### 3.3.6 Conclusion of Tramline Example

The monitoring chart for the Houston Tram illustrates how effective an appropriate HIA with proper monitoring system can be. If this monitoring chart had been utilized by the light rail company in Houston, safety measures could have been put in place quicker or an investigation of the rate of accidents may have been launched sooner.

## 3.4 Conclusion of Negative Health Impacts

The three example in this chapter were quite different from each other. However, they were all examples of a health impact assessment where a negative impact on the health of the public is expected. The monitoring chart in each case showed the effectiveness of continuously monitoring health events, even after a HIA has been carried out.

The public health monitoring of suicide is important, especially the detection of seasonal clusters. A seasonal cluster of suicides was found in males aged 20-29, this suggests that extra support services should be available in the high risk months and targeted towards young men. A cluster of suicides by hanging could be indicative of a copycat suicide problem. However further in-depth investigation is required to confirm this cluster as copycat suicides.

While the incinerator example was essentially illustrative of a monitoring system for HIA, it did show that the Poisson scan statistic is appropriate to use as a monitoring tool. An important aspect of this example was the rarity of the cancer events. It was not sensible to use a short window of less than 3 months and so to accommodate the rare events a window of at least half a year was used. This

shows that even for rare events the scan statistic is appropriate. It also emphasises the importance of choosing an appropriate window width, as outlined in Chapter 2. A smaller window would have been futile in this example and would have resulted in a useless monitoring chart.

In the tram example, the scan statistic was setup to monitor tram accidents using 'real-life' data. This illustrated the benefit of a HIA on something apparently unrelated to health - such as a new transport system. The monitoring within the HIA detected clustering of accidents, while not all accidents will result in injuries to people all accidents have the potential to be harmful. This example illustrates how monitoring LUAS data would be useful.

# Chapter 4

# Positive Health Impacts

Not all health impacts will be negative. The advantage of carrying out a health impact assessment on all relevant proposed policies is to make appropriate changes, so that any negative health impacts can be anticipated and adjustments made. On the other hand if there are no suspected negative health impacts perhaps a change can be made so that positive impacts on health can be achieved. Just as suspected negative health impacts are monitored, it is important that positive health impacts are monitored to ensure that the expected pluses do occur.

Positive health impacts would be expected when a new hospital is opened, a pedestrian bridge is built across a busy motorway or a scheme is put in place to reduce AIDS cases. In this chapter two cases where positive health impacts might be expected will be examined. The first is examining the effect of the smokey coal ban in 1990 in various cities around Ireland. The second is examining the effect of the penalty points introduction for speeding in Ireland.

## 4.1 HIA of the Bituminous Coal Ban in Dublin

### 4.1.1 Screening

Bituminous fuel can result in a smog that is a mixture of smoke emitted when bituminous coal is burned. Bituminous fuel along with exhaust fumes from motor vehicles are the main sources of smog [99]. In Ireland, 1987 figures for smoke emissions by fuel showed that $93.58\%$ of coal smoke came from domestic heating systems, $4.48\%$ from power generation and $1.94\%$ from industrial coal burning. This indicates that domestic fuel smoke is one of the biggest source of smoke emissions.

The ban on the sale, marketing and distribution of smokey coal should have a positive health impact. As the ban will be extended to many other areas a health impact assessment is imperative. Given that the Solid Fuel Trade Group had problems with the ban, evidence of positive health impacts could lead the way for a nation-wide ban.

### 4.1.2 Scoping

Even at low concentrations smog pollution can result in annoyance, minor eye irritations, "chestiness" and aggravation of symptoms for asthmatics and people with sinusitis, bronchitis, colds, flu or other respiratory disorders. At higher levels smog can be fatal. This is demonstrated by the increase in deaths among people with respiratory disease during periods of increased smog levels.

In London in the winter of 1952 the "Great Smog" resulted in many casualties. From $5^{th}$ December through $9^{th}$ December 1952 a heavy, motionless layer

of smokey, dusty fumes from the region's million or more coal stoves and local factories settled in the London basin. The undertakers and florists were the first to be aware of a health problem in the city: they ran out of caskets and flowers [100].

Health officials at the time did not appreciate the magnitude or severity of the problem, having previously weathered many dense "pea-souper" fogs and smogs. Hospital admissions, pneumonia reports, applications for emergency bed service, and mortality followed the peak of air pollution. Mortality remained elevated for a couple of months after the fog [100]. At least 4000 deaths have been attributed to the "Great Smog of London".

In the 1980s, in Dublin, there was a switch from oil to the cheaper and more widely available solid fuel, mainly bituminous coal, and so the air quality in Dublin deteriorated [101]. Periods of high air pollution were associated with increased in-hospital respiratory deaths [102]. A study by Clancy et al [103] found that black smoke concentrations in Dublin declined by 70% after the bituminous coal ban and that this led to a 15% decrease in respiratory deaths.

Regulations were made in 1990 to ban the marketing, sale and distribution of bituminous coal in the Dublin area [104]. This intervention meant an immediate reduction in average monthly particulate concentrations [105]. The ban was extended to Cork in 1995 and extended to five additional areas in 1998 (Arklow, Drogheda, Dundalk, Limerick and Wexford). Further extension of the ban to five new areas (Celbridge, Galway, Leixlip, Naas and Waterford) took place in October, 2000.

The Solid Fuel Trade Group, which represents traders of solid fuel, disagreed with the Governments proposals for a nationwide ban of bituminous fuel. A negotiated agreement was signed by the Department of the Environment and the Solid

Fuel Trade Group in 2002 which contained a reduction in the sulphur content of bituminous coal and petcoke and the extension of the ban on the marketing, sale and distribution of solid fuels. Amongst the principal features of the negotiated agreement are:

- Phased increasing penetration of (minimum 25% of total sales) of smokeless fuels in 8 areas (Athlone, Bray, Carlow, Clonmel, Ennis, Kilkenny, Sligo, Tralee) from 1 October 2002.

- Outright ban on the sale of bituminous coal in Bray, Kilkenny, Sligo and Tralee from 1 October 2003.

- Penetration of smokeless fuel in the remaining towns (Athlone, Carlow, Clonmel and Ennis) to increase to 75% by 1 October 2004.

### 4.1.3 Appraisal

A positive health impact on respiratory deaths arising from the ban on smokey coal in Dublin will be investigated. Smog affects the lungs and there is evidence to suggest that it increases the number of respiratory deaths. Respiratory disease data are extremely seasonal. Much work has been conducted about the fact that there is excess winter mortality - in the case of respiratory disease the effects of winter exacerbate the respiratory deaths.

Appendix C shows a report detailing the problem of excess winter mortality in Ireland and it also outlines various models which were used to model the excess winter mortality.

As there is a larger proportion of people using coal in the winter, due to colder climate, this may be one cause of more people dying from respiratory diseases. A result of this may be that when the health impact of smokey coal is looked at, only a positive impact in the winter months may be found with no impact in the summer months. People who die of respiratory disease in summer are likely to be dying as a result of something other than smokey coal and smog.

**Seasonal Data**

One of the main assumptions of the scan statistic is a constant population at risk and a constant detection rate of cases. In the case of health events this is often not the case, and it is important to be able to overcome this restrictive assumption.

Although the ratchet scan has been used to scan seasonal data in previous sections, it is not appropriate to use when the seasonality is a dominant source of variation in the data.

There are a number of ways to address seasonal data. Two of the methods of assessing the data for a cluster will be looked at here. The first method that will be examined is possibly the simpler of the two methods and involves deseasonalising the data and then scanning it as outlined in Chapter 2. The second approach uses a method outlined by Kulldorf [106] which involves fitting an appropriate model to the data and using a generalized likelihood ratio to test the null hypothesis that there is no clustering of events. In order to assess these methods they will initially be used to look for a cluster of events, as in Chapter 3. Then a dip in events will be monitored.

**Deseasonalised Data Method** One way of coping with data that has a strong seasonal element is to deseasonalise the data. This can be achieved using the classical moving average method. The method involves the following simple steps:

1. Compute a simple moving average. For example if data are available on a daily basis, to compute a 365 day moving average, the average of the first 365 days is calculated and then moved on one day, and again the average is computed over the next 365 days and so on.

2. If the moving average in step 1 was not centred, in this step centre the moving average by calculating a moving average using groups of 2.

3. Compute the seasonal error component. This can be achieved by dividing the observed value by the centred moving average, calculated in step 2.

4. Calculate the unadjusted seasonal index. This is the average of the seasonal error component for each season.

5. Compute the adjusting factor by dividing the unit time by the sum of all calculated unadjusted seasonal indexes.

6. The adjusted seasonal index is computed by multiplying the unadjusted seasonal index by the adjusting factor.

7. Deseasonalised data are calculated by dividing the original observed data by the adjusted seasonal index.

These steps are illustrated using the monthly totals of respiratory mortality data for the years 1991-1992. Data are aggregated at a month level, so moving average will be calculated over 12 values. The first value for moving average is

the average of the first twelve months, the second value is the average of the 12 month period from February 1990 to January 1991. The centred moving average is calculated as the average in groups of two. The percent moving average is *Observed* divided by *% Moving Average* ($\%MA$). For these first few stages see Table 4.1

Once the $\%MA$ has been calculated then the seasonal index can be calculated. In this example only two years are being used, normally at this stage the average $\%MA$ would be calculated for each month, but since there is only one value of $\%MA$ for each month in this situation the average is not calculated. The adjusting factor is calculated by dividing the total number of time units (12 months) by the sum of the average $\%MA$ (12.036). The adjusted seasonal index is computed by multiplying the adjusting factor by $\%MA$. The final stage is to divide the observed data by the adjusted seasonal index to give the deseasonalised data in Table 4.3.

Figure 4.1 shows the daily data that has been deseasonalised using the method outlied above, and then summed for a three-month scanning window. As there is a lot of variation between the seasons even the deseasonalised data are still somewhat seasonal. There does seem to have been a shift downwards in the number of respiratory deaths in 1987.

Using the Binomial Scan statistic to investigate any clusters, in this time period, prior to the ban on smokey fuel, the largest cluster in a 91 day window was 368 respiratory deaths, which occurred between February and April 1986. The binomial scan statistic suggests that this is significant.

| yy | mm | Respiratory Deaths | Moving Average (MA) | Centred Moving Average (CMA) | % Moving Average (%MA) |
|---|---|---|---|---|---|
| 90 | 1 | 136 | | | |
| 90 | 2 | 83 | | | |
| 90 | 3 | 75 | | | |
| 90 | 4 | 66 | | | |
| 90 | 5 | 64 | | | |
| 90 | 6 | 53 | 69.833 | | |
| 90 | 7 | 59 | 67.250 | 68.542 | 0.861 |
| 90 | 8 | 53 | 67.667 | 67.458 | 0.786 |
| 90 | 9 | 52 | 67.583 | 67.625 | 0.769 |
| 90 | 10 | 51 | 66.750 | 67.167 | 0.759 |
| 90 | 11 | 61 | 67.167 | 66.958 | 0.911 |
| 90 | 12 | 85 | 67.583 | 67.375 | 1.262 |
| 91 | 1 | 105 | 67.500 | 67.542 | 1.555 |
| 91 | 2 | 88 | 66.583 | 67.042 | 1.313 |
| 91 | 3 | 74 | 67.167 | 66.875 | 1.107 |
| 91 | 4 | 56 | 67.250 | 67.208 | 0.833 |
| 91 | 5 | 69 | 68.167 | 67.708 | 1.019 |
| 91 | 6 | 58 | 66.250 | 67.208 | 0.863 |
| 91 | 7 | 58 | | | |
| 91 | 8 | 42 | | | |
| 91 | 9 | 59 | | | |
| 91 | 10 | 52 | | | |
| 91 | 11 | 72 | | | |
| 91 | 12 | 62 | | | |

Table 4.1: Moving Average Calculation

| mm | %MA | Adjusting Factor | Adjusted Seasonal Index |
|---|---|---|---|
| 1 | 1.555 | 0.997 | 1.550 |
| 2 | 1.313 | 0.997 | 1.308 |
| 3 | 1.107 | 0.997 | 1.103 |
| 4 | 0.833 | 0.997 | 0.830 |
| 5 | 1.019 | 0.997 | 1.016 |
| 6 | 0.863 | 0.997 | 0.860 |
| 7 | 0.861 | 0.997 | 0.858 |
| 8 | 0.786 | 0.997 | 0.783 |
| 9 | 0.769 | 0.997 | 0.766 |
| 10 | 0.759 | 0.997 | 0.757 |
| 11 | 0.911 | 0.997 | 0.908 |
| 12 | 1.262 | 0.997 | 1.257 |
| | 12.036 | | |

Table 4.2: Seasonal index computation

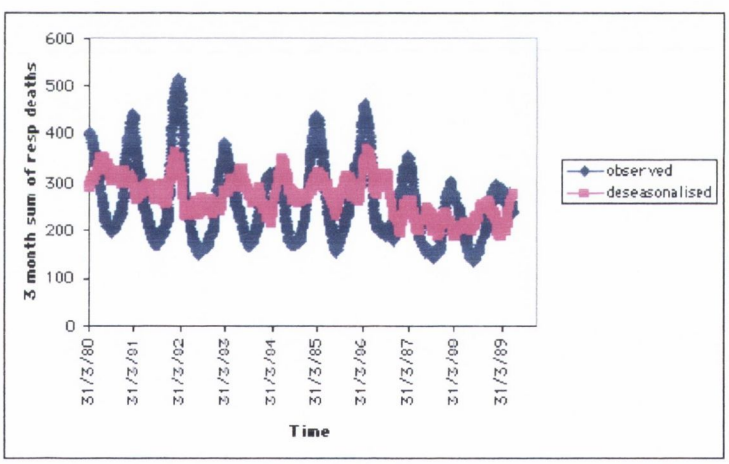


Figure 4.1: Deseasonalized daily respiratory data.

| yy | mm | Respiratory Deaths | Adjusted Seasonal Index | Deseasonalised data |
|---|---|---|---|---|
| 90 | 1 | 136 | 1.550 | 88 |
| 90 | 2 | 83 | 1.308 | 63 |
| 90 | 3 | 75 | 1.103 | 68 |
| 90 | 4 | 66 | 0.830 | 79 |
| 90 | 5 | 64 | 1.016 | 63 |
| 90 | 6 | 53 | 0.860 | 62 |
| 90 | 7 | 59 | 0.858 | 69 |
| 90 | 8 | 53 | 0.783 | 68 |
| 90 | 9 | 52 | 0.766 | 68 |
| 90 | 10 | 51 | 0.757 | 67 |
| 90 | 11 | 61 | 0.908 | 67 |
| 90 | 12 | 85 | 1.257 | 68 |
| 91 | 1 | 105 | 1.550 | 68 |
| 91 | 2 | 88 | 1.308 | 67 |
| 91 | 3 | 74 | 1.103 | 67 |
| 91 | 4 | 56 | 0.830 | 67 |
| 91 | 5 | 69 | 1.016 | 68 |
| 91 | 6 | 58 | 0.860 | 67 |
| 91 | 7 | 58 | 0.858 | 68 |
| 91 | 8 | 42 | 0.783 | 54 |
| 91 | 9 | 59 | 0.766 | 77 |
| 91 | 10 | 52 | 0.757 | 69 |
| 91 | 11 | 72 | 0.908 | 79 |
| 91 | 12 | 62 | 1.257 | 49 |

Table 4.3: Deseasonalized data computation

**An Optimal Test** Kulldorff and Nagarwalla [106] outline an optimal test statistic. Let $0 \leq t_1 \leq t_2 \leq \ldots, \leq t_N \leq T$ be the ordered times of the observations.

The generalised ratio test for testing the null hypothesis against the alternative rejects $H_0$ for large values of $S = \max_{i=1,\ldots,N} LY_{t_j}(w), E[Y_{t_j}(w)], t_j < T - w$, where

$$L[O,E] = \begin{cases} O\ln(O/E) + (N-O)\ln[(N-O)/(N-E)], & O > E \\ 0 & otherwise \end{cases} \tag{4.1}$$

Using equation 4.1 the occurrence of respiratory deaths was simulated according to a nonhomogeneous Poisson process. Using these simulated values as 'observed' values, the likelihood ratio test could be calculated and the probability of a maximum test statistic calculated. The simulation was repeated 2000 times using VBA Excel and the code as outlined in the appendix.

For the example of respiratory deaths, a seasonal model as outlined in appendix C was used. This particular model incorporates individuals who are over 35 years of age, died of respiratory illness (ICD code 480-519), in Dublin between the years 1980-1989. This period of time was used to estimate the parameters of the model as a ten-year period of time should ensure a good estimate of the seasonality. This period of time is also ten years prior to the introduction of the ban on smokey fuel. The model for these data is:

$$Y_t = 2.84 + 1.09\cos(\frac{2\pi}{365.25}t) + 0.69\sin(\frac{2\pi}{365.25}t) \tag{4.2}$$

Respiratory deaths over a two year (730 day) period were simulated and this simulation was repeated 2000 times.

For each of the simulations a window of three months was used as a scanning

window. Once these values were calculated then equation 4.1 was used to estimate the maximum test statistic for each simulation. The level at which the test statistic became significant could then be estimated as the test statistic greater than or equal to 5% of all the maximum values in the simulation. The simulation found that the test statistic was significant for $s' > 6.36$, where $s'$ is the maximum value found using equation 4.1 . Using this information the respiratory data can be scanned for any significant clusters.

The two-year period prior to the smokey coal ban will be scanned for any significant clustering. This means that for each 3 month period the test statistic (as given in equation 4.1) is calculated. If the test statistic exceeds 6.36 then a significant cluster has been found. The test statistic is plotted against time in Figure 4.2, where a red line represents the significant value.

Figure 4.2 shows that there is a significant cluster of respiratory deaths at the end of 1989. This corresponds to a period in December 1989 when the smog levels in Dublin were up to four times the safety limits set by the European Community. It was this increase in smog levels which sparked governmental debate in the upper house of the parliament (Seanad Eireann) which led to the bituminous coal ban the following September [107].

**Decrease Since Smokey Coal Ban Introduction?**

To investigate if there has been a reduction in respiratory deaths, since the ban on smokey fuel, Kulldorffs method as outlined in equation 4.1 on page 95 can be employed. Now if an observed value is significantly less than an expected value this would indicate a significant dip or decrease in the occurrence of events. The

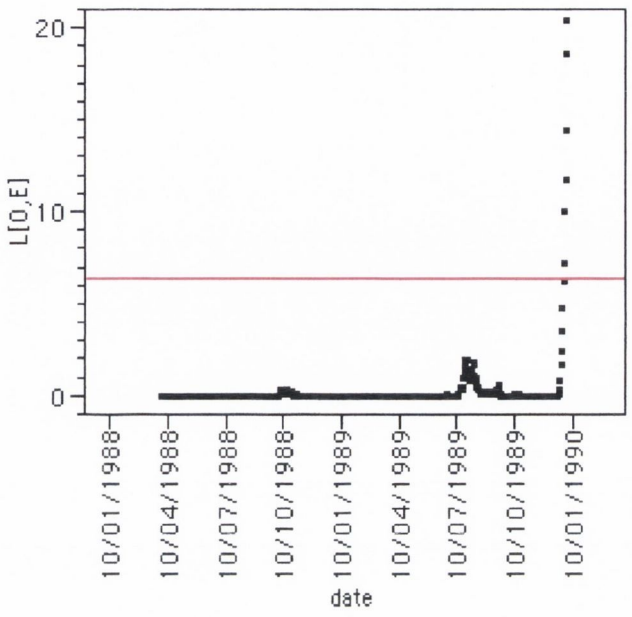


Figure 4.2: Using the optimal test for seasonality.

same test statistic can be used.

$$L[O,E] = \begin{cases} O\ln(O/E) + (N-O)\ln[(N-O)/(N-E)], & O < E \\ 0 & otherwise \end{cases} \tag{4.3}$$

To illustrate that the above test statistic will be optimal at detecting dips a simple scenario will be created. Suppose that in scenario 1 the observed value is 150, the expected value is 80 and total value is 550. In the second scenario the observed and expected values have been switched, so the observed value is 80 and the expected value is 150, the total remaining the same. The test statistic value is approximately the same for the two scenarios. This means that the test

statistic is equally efficient when detecting clusters or dips. Using this method a good approximation of the significance of a dip in the number of events could be estimated.

**Monitoring for a Dip in Respiratory Deaths**

It is of interest to see if the smokey coal ban has resulted in a decrease in respiratory deaths. To investigate this possible health benefit a monitoring system will be devised using Kulldorfs optimal statistic [106]. The smokey coal ban was introduced in September 1990, so a dip should be seen soon after that. The simulations that were carried out in section 4.1 can be used to pinpoint the value at which the test statistic is significant. This value can then be used as a type of control limit for the monitoring graph. For a significance level of 0.05, the appropriate test statistic is 5.28, this means that 5% of all simulated values were greater than or equal to 5.28. This is the value that is shown as the control line in Figure 4.3, values falling above this line indicate a decrease in respiratory deaths.

Figure 4.3 shows the test statistic plotted against date. A three months scanning window was used, scanning for a minimum in this instance rather than a maximum cluster. The blue dots in the graph represent the time since the ban on smokey coal was introduced.

In Figure 4.3 any points above the horizontal critical line indicate a significant decrease in respiratory deaths from the expected. It is obvious in the graph that there appears to be a significant decrease in respiratory deaths even before the ban on bituminous coal. The other significant decreases appear in April of 1989 and April - July 1990. The reason for the decrease in deaths at this point is that the model that was used overestimated mortality in the summer months. This method

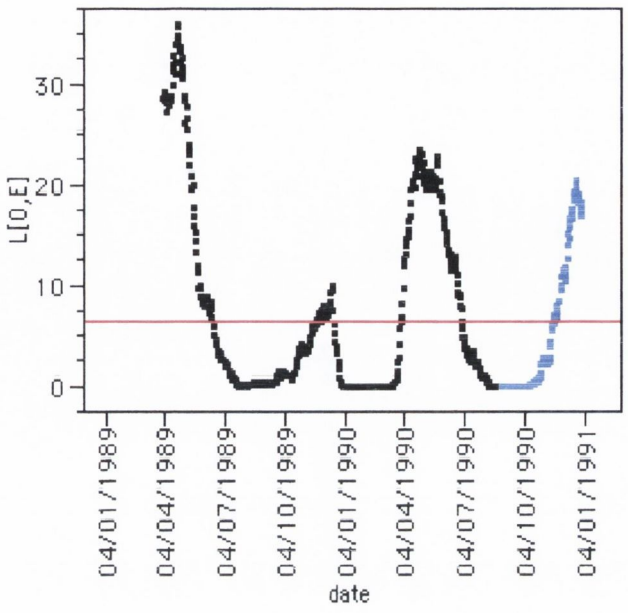


Figure 4.3: Using the optimal test for seasonality to detect a dip in respiratory mortality.

is heavily dependent on an accurate model.

It is clear from the graph that the winter of 1991 is the first winter period to show a significant decrease in respiratory deaths. Hence it can be stated with some certainty that the ban on bituminous coal had a positive benefit on health.

### 4.1.4 Conclusion

The respiratory data had a strong seasonal component which meant that some adjustment had to be made prior to scanning the data. Deseasonalising the data is one approach to taking away a strong seasonal element. Using this method eliminated the need to specify winter months which is the traditional method of

looking at excess winter mortality, as outlined in the Appendix.

The other approach taken was to model the data. Then using this model and an appropriate critical value which had to be estimated, a monitoring chart could be setup. This method also eliminates the need to specify winter months. This approach worked reasonably well. However, an extremely good-fitting model is required in order for the method to function optimally. In reality, it will be near impossible to fit an accurate model to 'real' data, thus applying Kulldorfs Optimal model will seldom be a good approach to coping with seasonal data. Real data cannot be modelled accurately from year to year as there are so many factors impacting on seasonality, it would therefore be more prudent to deseasonalise the data as discussed in section 4.1.3.

The findings of this analysis agree with the study conducted by Clancy et al [103]. However, while both studies could detect a decrease in respiratory deaths, by using the scan statistic the moment that respiratory deaths started to decrease is known. By correctly setting up the scan statistic as a monitoring chart immediate benefits are seen, rather than waiting for a number of years to get enough data to publish results.

## 4.2 Health Impact Assessment of the Penalty Point Introduction in Ireland

The coverage of road accidents in the media is an almost daily occurrence. Headlines such as "Seven people die in weekend accidents", "Five die over weekend from road accidents" and "Not enough done to end road carnage" have become commonplace amongst all the daily newspapers.

### 4.2.1 Screening

As part of a new road safety initiative in Ireland, penalty points for speeding were introduced from the $31^{st}$ October 2002. This new initiative meant that any individual caught speeding could be awarded up to four penalty points. Penalty points remain on a driver's licence for a period of three years, and an accumulation of 12 penalty points in a three-year period will lead to automatic disqualification from driving for 6 months. In a press release at the time the Minster for Transport, Samus Brennan TD, stated "Excessive speed is recognised as the most significant contribution to road accidents ...I am confident that it [penalty points] will assist in reducing the level of road deaths and serious injuries by instilling greater caution in drivers." [108]

Penalty points have been introduced subsequently for driving without insurance. As of $1^{st}$ June 2003 drivers convicted of driving without insurance will incur five penalty points in addition to a fine imposed by the court. On $25^{th}$ August 2003 penalty points for seat belt offences were introduced. Penalty points for careless driving was effective from $4^{th}$ June 2004.

### 4.2.2 Scoping

The National Roads Authority [109] published a report in November 2003. They revealed that single vehicle collisions were reported in 30% of all road fatalities. Single vehicle collisions are linked with speeding and driving under the influence of alcohol. Drivers were cited by the police as the main contributing factor in 86% of accidents in 2002. This evidence suggests that penalty points may help change driver attitude and reduce the carnage on the roads.

Since the introduction of penalty points, more recent press coverage has hinted at a levelling-off of the effect of penalty points in the reduction of road fatalities. The scan statistic will be used to investigate if there was any clustering of road fatalities prior to the penalty point introduction. It will then be implemented as a monitoring tool to investigate if there was a positive or negative impact on the number of road fatalities.

### 4.2.3 Appraisal

The National Road Safety Authority (NRSA) compiles an annual statistical report on road fatalities and accidents, based on data supplied by the Garda Siochana. In the last year the method by which the NRSA were informed of non-fatal road accidents changed. There are teething problems with the new system with the result that the data are not always entered into the database. Analysis on the non-fatal road accident data are not possible because the data are unreliable. Road fatality data are available on the Garda Siochana website. The data are aggregated by month - further contact with the Road Traffic Bureau revealed that the data are not available on a daily basis. The Road Traffic Bureau did reveal that the daily

rate averaged out at one fatality per day.

Data on monthly totals of road fatalities were obtained from the Garda website. Table 4.4 shows the average number of fatalities per month for the years 1998 to the introduction of penalty points (November 2002). Available on the Garda webpage are collision statistics for the years 1968-2002. The probability of being injured or killed in a serious accident, between 1998-2001, before the introduction of penalty points, was 0.003, given that an individual was involved in a serious accident the probability of being killed in the accident was 0.035. Prior to the introduction of penalty points, the probability of an individual being killed in a traffic accident was 0.0001.

| year | Average |
|---|---|
| 1998 | 38 |
| 1999 | 34 |
| 2000 | 35 |
| 2001 | 34 |
| 2002 | 33 |

Table 4.4: Average monthly number of road fatalities prior to penalty points.

It is of interest to know if the introduction of penalty points for speeding had an impact on the number of fatalities. The data are grouped by month so the ratchet scan statistic is an obvious choice to investigate this health impact. However, the quantities of road fatalities are large. This results in a large $N$, annual figure, thus the asymptotic distribution of the ratchet scan (section 2.5.3, page 43) will be used. A three-month scanning window will be used.

In the year that penalty points were introduced there was a total of 376 ($N$) fatalities on the road. The distribution of these road deaths is in Table 4.5. A

| Month | Fatality Frequency |
|---|---|
| January | 35 |
| February | 33 |
| March | 34 |
| April | 32 |
| May | 20 |
| June | 34 |
| July | 42 |
| August | 35 |
| September | 36 |
| October | 31 |
| November | 23 |
| December | 21 |

Table 4.5: Distribution of Road Fatalities in 2002.

three-month scan of the data, looking for the maximum cluster, gives a cluster ($T^3$) of 113 deaths. This maximum cluster of deaths occurred between July and September of 2002. The ratchet scan statistic was calculated using equation 2.12 (page 47):

$$R^3 = \frac{113 - 1 - 376(0.25)}{\sqrt{376(0.25)(1 - 0.25)}} = 2.1438 \tag{4.4}$$

Using the value of $R^3$ obtained in 4.2.3 the probability of a cluster can be estimated, using Figure 2.7. From the graph the probability of a cluster of 113 fatalities in the year 2002 was approximately 0.12. This was not a significantly large number of road fatalities prior to the introduction of penalty points. As a three month scanning window was used, it also indicates that there was no seasonality associated with road fatalies.

### 4.2.4 Decision Analysis

There is no evidence of significant seasonal clustering of road accidents. As was found in the scoping phase of this HIA, many accidents are caused by speeding. The introduction of penalty points should reduce the number of fatal road accidents. Road accidents should be monitored to ensure that this expected health improvement happens. To do this the data for the year 2002 will be scanned looking for a dip in traffic accident fatalities. If the penalty points were a success then a significant dip, post penalty point introduction, should be expected.

### 4.2.5 Monitoring and Evaluation

In order to use the scan statistic to find a dip in the number of road fatalities, the ratchet scan statistic must first be adjusted so that it will scan for 'dips' rather than clusters. Just as there can be a cluster of events, where an increase in events is observed, there can also be a 'dip' in the number of occurrences of an event. A dip would be recognised as being an unusually small number of events occurring. As a cluster might indicate an increase in something such as cancer cases, a dip would be a useful indicator in the success of a new health initiative.

#### Dip in Occurrence of Events

To investigate the possibilities of dips in frequent events, some of the theory already discussed in section 2.5.3 will be applied. Using the multinormal vectors that were created to estimate the ratchet scan statistic in section 2.5.3, the minimum value from each $(Z_1^k, Z_2^k, \ldots, Z_{11}^k, Z_{12}^k)$ vector was selected instead of the maximum that was used before.

Let $D_\alpha^k$ be the $\alpha$th percentile of minimum $Z_i^k$, then applying the theory in Wallenstein et al [74], the following should hold true, where U is the minimum dip in a given time period:

$$U_\alpha^k(N) = \frac{Nk}{12} + \sqrt{N} D_\alpha^(k) \sqrt{\frac{(12-k)(k)}{144}} \tag{4.5}$$

To evaluate the adequacy of this asymptotic result at $\alpha = .05$, the value of for each of the multinomial vectors was used. The results are given in Table 4.6. The asymptotic estimates of $U_{0.05}$ are good approximations of the simulated $U_{0.05}$ values.

This finding is somewhat unexpected when Table 2.1 is considered. It shows the scan statistic values for clusters, in table 2.1 there was a difference of approximately 1. Using this evidence the P-value can be mapped onto the ratchet scan statistic using the following:

$$D^k = \frac{U^k - Nw_k}{\sqrt{Nw_k(1-w_k)}} \tag{4.6}$$

Figure 4.4 shows the ratchet statistic for a dip, over a one-month period. The asymptotic distribution does not approximate the simulated N curves accurately. P-values for $N = 250$-$1000$ are similar to each other. However the p-values for an $N = 100$ are quite different. For a window size of 2 months (see Figure 4.5), the asymptotic distribution is a better estimator of p-values for $N \geq 250$. Again if $N < 250$ then perhaps the curve for $N = 100$ should be used, or another

| | | Asymptotic Theory | | Simulation | | | | |
|---|---|---|---|---|---|---|---|---|
| k | N | $U_k(0.05)$ | $\frac{U_k(0.05)}{N}$ | n | $P(U_k > n)$ | $P(U_k > n+1)$ | $\frac{t}{N}$ | $U_{0.05}$ |
| 1 | 50 | -0.9806 | -0.0196 | 0 | 0.1377 | - | - | - |
| 1 | 100 | 1.0541 | 0.0105 | 2 | 0.0835 | 0.0179 | 0.0149 | 1.4893 |
| 1 | 250 | 9.3238 | 0.0373 | 10 | 0.0536 | 0.0226 | 0.0395 | 9.8839 |
| 1 | 500 | 25.3897 | 0.0508 | 27 | 0.0791 | 0.0458 | 0.0523 | 26.1261 |
| 1 | 1000 | 60.3142 | 0.0603 | 62 | 0.0678 | 0.0462 | 0.0612 | 61.1759 |
| 1 | 2000 | 134.1128 | 0.0671 | 135 | 0.0509 | 0.0389 | 0.0675 | 134.9250 |
| 2 | 50 | 1.4434 | 0.0289 | 2 | 0.0709 | 0.0138 | 0.0327 | 1.6340 |
| 2 | 100 | 6.9228 | 0.0692 | 8 | 0.0953 | 0.0385 | 0.0720 | 7.2025 |
| 2 | 250 | 26.2603 | 0.1050 | 27 | 0.0651 | 0.0368 | 0.1059 | 26.4664 |
| 2 | 500 | 61.5455 | 0.1231 | 62 | 0.0536 | 0.0363 | 0.1236 | 61.7919 |
| 2 | 1000 | 135.8540 | 0.1359 | 137 | 0.0619 | 0.0477 | 0.1362 | 136.1620 |
| 2 | 2000 | 289.7576 | 0.1449 | 291 | 0.0593 | 0.0491 | 0.1450 | 290.0882 |
| 3 | 50 | 4.5589 | 0.0912 | 5 | 0.0666 | 0.0205 | 0.0928 | 4.6399 |
| 3 | 100 | 13.7696 | 0.1377 | 14 | 0.0539 | 0.0263 | 0.1386 | 13.8587 |
| 3 | 250 | 44.7431 | 0.1790 | 45 | 0.0505 | 0.0332 | 0.1799 | 44.9711 |
| 3 | 500 | 99.8880 | 0.1998 | 100 | 0.0512 | 0.0385 | 0.1998 | 99.9055 |
| 3 | 1000 | 214.4863 | 0.2145 | 216 | 0.0611 | 0.0491 | 0.2151 | 215.0750 |
| 3 | 2000 | 449.7760 | 0.2249 | 451 | 0.0558 | 0.0480 | 0.2251 | 450.2564 |

Table 4.6: Results of asymptotic simulations, compared with simulations for different values of N.

curve sketched in. As was also found for clusters in Chapter 2, the graph for a window of 3 months (Figure 4.6) shows that the asymptotic distribution is a good approximation for $N \geq 100$.

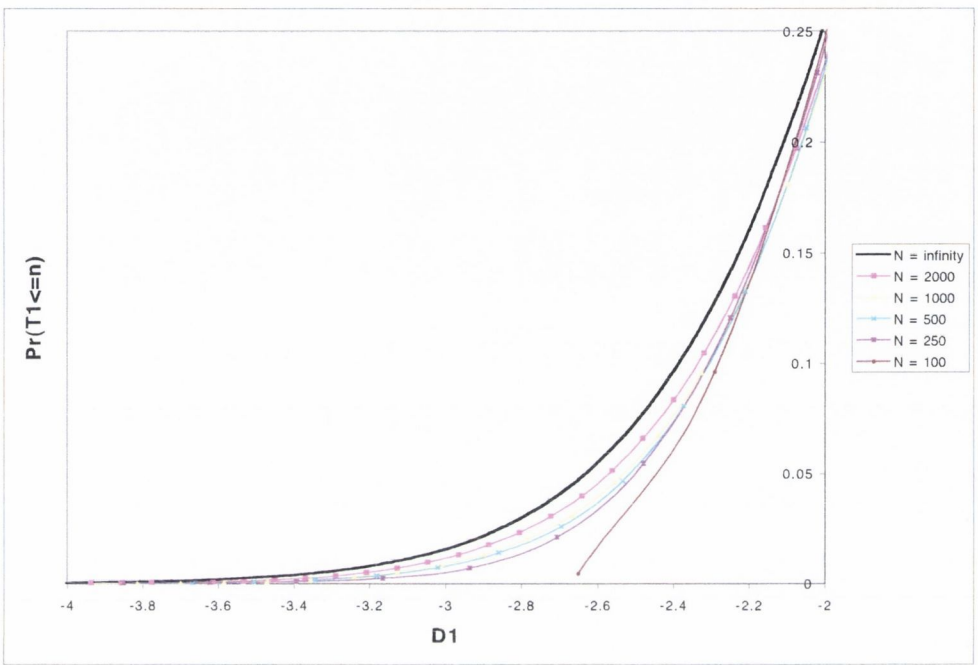


Figure 4.4: Scan statistic for a dip in events, with a window of 1 month.

To see if there is a reduction in fatalities, the three-month window incorporating November 2002 (the first month of penalty points) is investigated to see if it indicates a significant dip in road fatalities. The number of fatalities between September and November 2002 was 90, which is not significant. This is probably because there are two months in which there were no penalty points included.

Moving on another month, the twelve month monitoring time period is now January to December 2002. There was a total of 376 fatalities, and the penalty

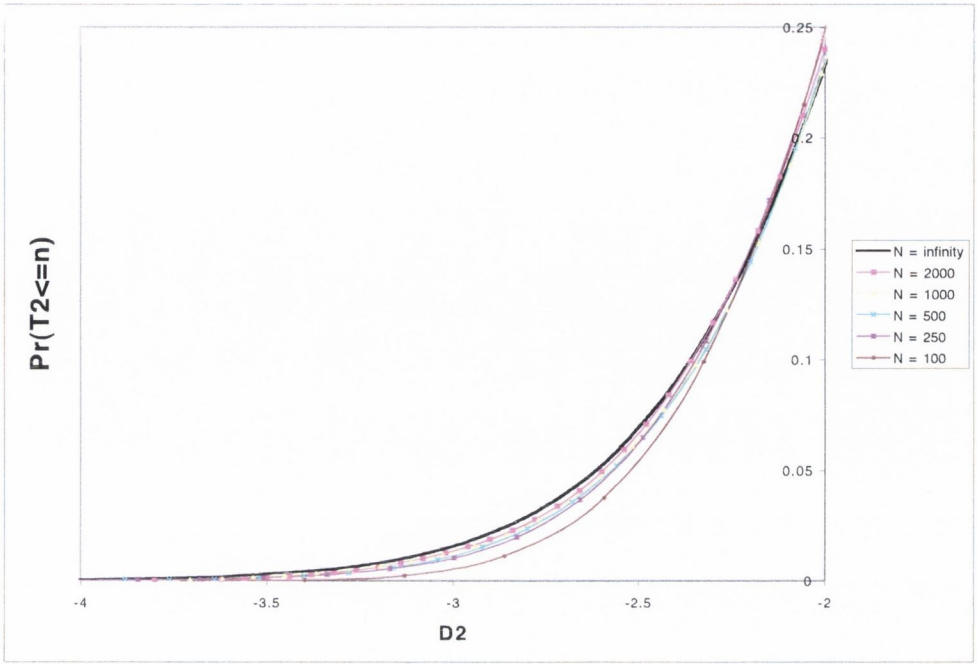


Figure 4.5: Scan statistic for a dip in events, with a window of 2 months.

point policy had been enforced for two months. Using a 3 month window and the most recent time period, October - December, there were 75 fatalities in this window but this was not significant at p=0.1125.

Moving on another month, the twelve-month period will now be from February 2002 - January 2003, the total number of fatalities in this time span is 361. The 3 month window that will be looked at is the window from November 2002 - January 2003. This is the first time point at which a three month window which only includes penalty point months can be examined, in other words all the months in this window are months when penalty points have been enforced.

The three months from November 2002 - January 2003 had a total of 64 fatali-

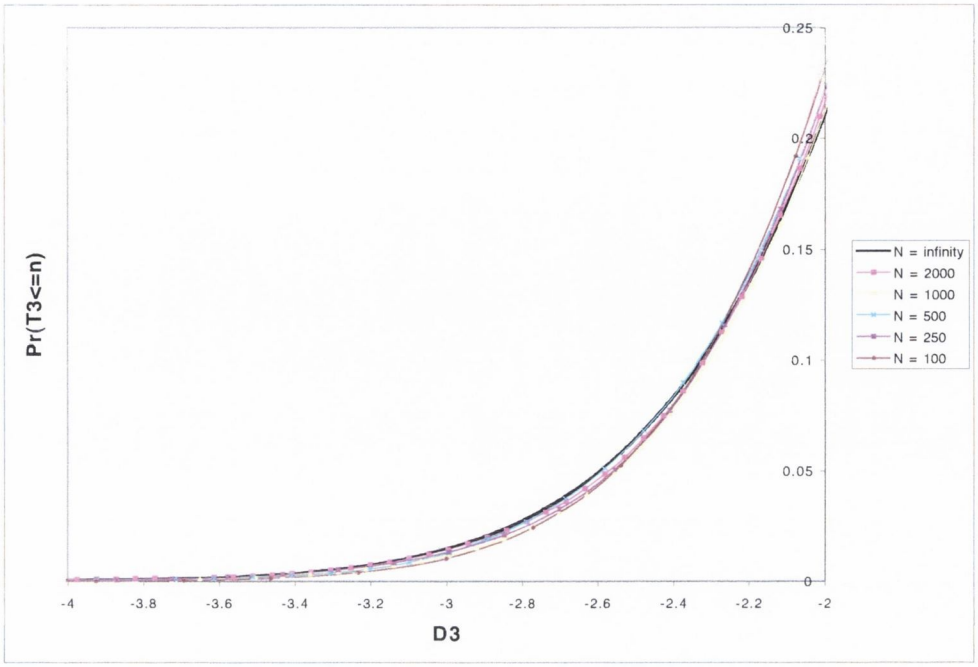


Figure 4.6: Scan statistic for a dip in events, with a window of 3 months.

ties. Using the ratchet scan statistic, it was found that this value shows a significant dip (p= 0.0125) in this 3-month period. As these 3 months are the only 3 months in this time period with penalty points, this is initial evidence that penalty points seem to be having a positive impact on health.

After three months of monitoring the road traffic fatalities there is evidence to suggest that penalty points are a success. However it is important to continue monitoring road fatalities, so that any further positive impact can be reported, thereby generating further support for the policy. It may be the case that the number of road fatalities begins to increase; the effect seen after 3 months could be an initial effect, as people become used to the policy and perhaps see little

evidence of speed cameras, garda checkpoints etc. The initial effect may wear off and people may start speeding again, or forget the new policy - it will have been given a high public profile in the early months.

If continued monitoring for peaks and troughs is carried out then continued success or failure can be reported and necessary adjustments to the policy put in place. For example if road deaths continue to decrease, perhaps speeding laws can be changed. If there are clusters then perhaps more speed cameras can be put in place and more visibility of police carrying out speed checks.

Figure 4.7 shows $D_3$ (the ratchet scan dip statistic for a three month window) calculated for a number of months and plotted on a graph. In this way it is possible to implement the ratchet scan statistic as a monitoring tool. A significance level of $P(T_3 \leq n) = 0.10$ was chosen; this corresponds to a $D_3$ value of approximately -2.36. So the shaded area in the graph would represent an 'alert' zone, or in this case a time period when a significant reduction in road accidents was observed.

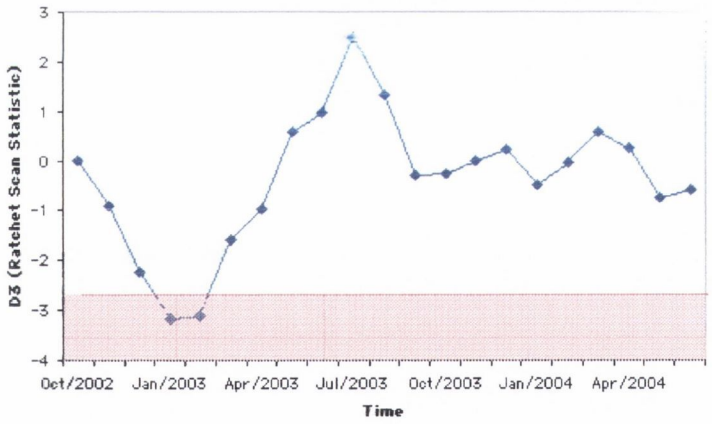


Figure 4.7: Monitoring for a dip in road deaths after penalty point introduction

In the graph, $D_3$ is plotted on the y-axis, and has been calculated as per equation 4.2.5. Time is plotted on the x-axis. So the value at Dec 2002 for example, means the value of $D_3$ calculated for the window from October to December 2002, using a total time period of January to December 2002. The value at January 2003 would mean the value of $D_3$ calculated for the 3-month window from November 2002 - January 2003, for the total time period February 2002 - January 2003.

There are two points in the alert zone, which means there were two occasions when a significant dip in road fatalities was observed. The first significant dip was between November 2002- January 2003 and it occurred during the first three months of the penalty points for speeding policy. The second dip occurs during the next three months (December 2002 - February 2003). There are no further dips in the data, this implies that there has been no more decreases in the accident mortality rate which means that the accident mortality rate has leveled off or that it has increased once again.

The calculation of the ratchet scan statistic involves the total number of fatalities in the most recent three month period and the total number of fatalities in the most recent 12 months. This means that the ratchet scan statistic for January 2003 involves 3 months of very low fatalities and 9 months of high fatalities - there are many more high fatality months, so a three month low period will certainly make a big impact.

By the time the monitoring is at March 2003, there are 5 penalty point months (low fatality months) and there are 7 non-penalty point months (high fatality months). The only possibility for obtaining a significant dip at this stage is for road fatalities to continue decreasing, in other words for the most recent 3 months to be continually getting smaller.

So from this stage on (March 2003), the graph can used to identify a continuing significant decrease in road fatalities. A continuing decrease will be alerted by the values falling in the red zone. A graph monitoring for clusters can also be used to check that there are no significant clusters of road accidents - which would be an indication that road fatalities were increasing. If there are no significant dips or significant increases it means that the road fatalities have decreased and are stabilized at a lower level and perhaps further changes need to be implemented to ensure further decreases in deaths on the road.

In Figure 4.8 $R_3$, the test statistic for a significant cluster was calculated and plotted on the y-axis, time is on the x-axis and is interpreted as described for the monitoring for a decrease graph. There is a significant increase in May - July 2003, this seems to indicate that the incidence of road fatalities has increased again. The initial effect of the introduction of penalty points has worn off.

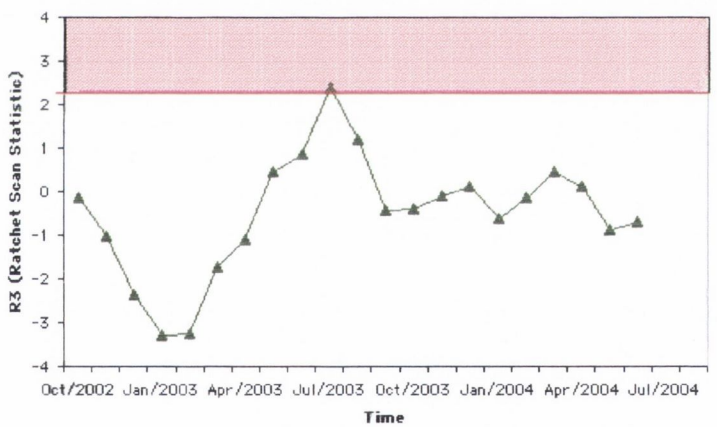


Figure 4.8: Monitoring for an increase in road deaths after penalty point introduction

Penalty points were introduced in June 2003 for having no valid insurance. If there is a real fear of penalty points another reduction in the number of road fatalities should have been observed - however as can be seen from the graph, Figure 4.7, there has been no significant reduction in fatalities.

Wearing of seat belts saves lives. With this in mind, on $25^{th}$ August 2003 the Minister for Transport introduced penalty points for not wearing seat. If a person was found not wearing a seat belt they could incur up to 4 points on their driver's license, and the driver of a vehicle will also incur points if there are any individuals under the age of 17 years not wearing a seat belt or restraint. However, looking at Figure 4.7, this life saving measure has not reduced the number of lives lost on the roads of Ireland.

The third set of penalty points were introduced on the 4th June 2004 for careless driving. However it is too soon to tell whether this policy will affect the number of road fatalities.

### 4.2.6 Conclusion

The monitoring of road fatalities in Ireland was possible using the ratchet scan statistic. As a decrease in road fatalities was expected after the introduction of penalty points it was necessary to monitor for this decrease. The monitoring in this example proved worthwhile. It showed that an initial decrease in road fatalities was followed by an increase in road fatalities, and this indicates that the penalty point system is not working in Ireland.

## 4.3 Conclusion

In the two examples examined in this chapter it was seen how necessary it is to monitor for positive health impacts. Evidence of a positive health impact in the case of the respiratory deaths gives the required evidence to enforce a nationwide ban on smokey fuel. In the case of the road fatalities it shows that an expected positive health impact means that the health events should still be monitored. In this case the monitoring showed that the health benefits were short-lived.

# Chapter 5

# Power Analysis of the Scan Statistic

The scan statistic has been used in the last two chapters to clarify if clusters or dips in events were identifiable. In some of the situations it was possible to use more than one type of scan statistic. In other cases such as the penalty point example, the available data restricted the possible methods that could be used.

In application of the scan statistic to HIAs there will be cases where the data available restrict the options for analysis. In such situations the following question may be asked: "Am I losing important information by having to use a particular method?" This chapter will examine the impact that any such restriction will have on the findings of the analysis.

There will likewise be situations when the data allow more than one choice of statistic. In this situation an appropriate question might be–"Which method is best to use?" The second part of this chapter will examine which method has the most power to detect clusters. The last section will examine the difference that the relative size of a cluster can have on marginal significance.

## 5.1 Aggregate the data?

Often data are only available on an aggregated basis, sometimes weekly, sometimes monthly. In the examples that have been discussed here, the data were available on a daily basis in most situations. However, there were instances such as the road deaths, where the data were only available on a monthly basis. An important consideration might be - what effect does this aggregation have on the analysis? Is important information being lost? It is not possible to determine what information has been lost due to aggregation of for example, road deaths. However, when daily data exist these can be aggregated and the effects of aggregation in this situation investigated.

It is still possible to implement the scan statistic on aggregated data; the ratchet scan statistic was developed for this purpose. However does the ratchet scan lose power? Perhaps further insight into the data can be gained by aggregating them, in which case daily data could routinely be aggregated.

### 5.1.1 Suicide Data

Supposing that the suicide data in Chapter 2 were not available on a daily basis but the data were only available as monthly totals.

The ratchet scan as outlined in Chapter 2, section 2.5.3 will be used for cluster detection and a window of three months will be used to scan the data. The largest cluster is 131 suicides and this cluster occurred between June and September. Using equation 2.12 in Chapter 2 the test statistic can be calculated as follows:

$$R^3 = \frac{131 - 1 - 810(0.25)}{\sqrt{810(0.25)(1 - 0.25)}} = 3.055 \tag{5.1}$$

This statistic can be used to find the p-value with the help of Figure 2.7 on page 50. From the graph it is possible to estimate the significance at 0.017.

By aggregating the data to a monthly level in this situation information was not lost, it was still possible to tell that there was a significant cluster of suicides between June and September of 1996. However, using the daily data may provide more accurate information as to the exact time period of the cluster which was between $5^{th}$ June 1996 and $3^{rd}$ September 1996.

### 5.1.2 Respiratory Mortality Data

If the respiratory deaths data had been available only at a monthly level, the first step may have been to deseasonalise the data as outlined in section 4.1.3.

The twelve months prior to the ban on smokey coal will be examined, September 1989 - August 1990. In that twelve months there was a cluster of 270 respiratory deaths between December and February. This corresponds to the cluster discussed in section 4.1.3, page 94 which was due to a heavy smog. There were 894 deaths in the 12 months in question. Using equation 2.12, page 47, the ratchet scan statistic for clusters, $R_k$ can be estimated as follows:

$$R^3 = \frac{270 - 1 - 890(0.25)}{\sqrt{894(0.25)(1 - 0.25)}} = 3.51 \tag{5.2}$$

From Figure 2.7 this corresponds to a p-value of approximately 0.005. This indicates a significant cluster, which can be explained by a heavy smog in Dublin city at that time, as discussed in section 4.1.3, page 96.

Continuing with a 3 month window, a dip after implementation of the smokey coal ban will be investigated. The window that contains the first month of the ban

revealed 216 deaths. Using equation 4.2.5, page 106 to estimate $D_3$, the ratchet scan test statistic for a dip in the data.

$$D_3 = \frac{216 - 896(0.25)}{\sqrt{896(0.25)(1-0.25)}} = -0.96 \tag{5.3}$$

Figure 4.6, page 110 tells us that -0.96 is not significant, which is not surprising as this window contains data from August and July when the ban was not in place.

Moving the scanning window on a little further, so that it incorporates the months September, October and November, the number of respiratory deaths in this period was 187 and there was a total of 883 deaths in the 12 month period December 1989 - November 1990. Evaluating $D_3$:

$$D_3 = \frac{187 - 883(0.25)}{\sqrt{883(0.25)(1-0.25)}} = -2.70 \tag{5.4}$$

$D_3 = -2.70$ corresponds to a p-value of approximately $0.05$, (Figure 4.6, page 110). This suggests that there was a significant decrease in respiratory deaths post implementation of the smokey coal ban.

The 12 month period after the implementation of the smokey coal ban was analysed to investigate an increase in the respiratory deaths. An increase in respiratory deaths might indicate that people were not obeying the ban and smokey coal was in use, or it could mean that the decrease in deaths after the ban was a fluke. It could also mean that people who would normally die in the winter from respiratory died at a later point in the year.

The maximum number of deaths in a three month period after the ban on smokey fuel was 211 which happened between January and March 1991. In the

twelve months following the ban 809 people died of respiratory disease. This is not a significant cluster, so it appears that the ban was obeyed. It also indicates that the respiratory deaths in winter are not some kind of 'culling of the weakest', an individual who avoids dying of respiratory disease due to smog in winter is unlikely to die the following summer.

### 5.1.3 Conclusion

In this case using monthly totals did not lose any important information, but it made the analysis somewhat more straightforward. The respiratory data were very variable, which implies that there was a lot of white noise in the daily data. Thus by using the monthly totals the day to day variability could be factored out. By doing this there was no loss of important information.

When a scanning window of more than a month is used it is reasonable to assume that any clusters will be observed whether data are aggregated at a monthly level or are available at a higher definition such as daily data. In the two examples a scanning window of three months was used, which is large enough not to hide clusters. In some cases such as the incidence of carbon monoxide poisoning, the clustering occurs in a small time frame, within 2-3 days. In such a situation monthly totals would be useless.

## 5.2 Power Analysis

In the previous chapters different versions of the scan statistic have been used in different situations. A variety of different data types were used and a version of the scan statistic was able to analyse each data set for cluster detection. However as all the examples were real examples the data were somewhat constraining so every version of the scan statistic could not be applied to every situation. For example in the case of accident fatality data which was only available at a monthly level the Binomial scan statistic could not be applied. As a result comparing the performance of the Binomial Scan statistic with the ratchet scan statistic could not be accomplished.

To compare the different scan statistics against each other and find where they perform best, a simple power analysis was undertaken. Artificial scenarios were developed and each form of the scan statistic applied to each situation. Using a multinomial distribution 1000 simulations of $\{n_1, n_2, \ldots, n_{365}\}$ was carried out for each of the scenarios outlined below, where $n$ is the number of events on any particular day.

Three different scenarios were formulated. The first scenario imitated a situation where there was a peak lasting one month. The second scenario simulated a situation where there was a peak that lasted a period of approximately 4 months. The last scenario simulated a situation where there were two peaks in a year, the two peaks being more than three months apart. By simulating these three scenarios data were created that could be used to check the power of each of the scan statistics. Each of the scenarios is shown below, in each case $P(e_i)$ is the probability of an event occuring.

Scenario 1: A peak of one-month duration.

$$P(e_1) = \begin{cases} 0.2136 & July \\ 0.0711 & otherwise \end{cases}$$

Scenario 2: A peak lasting four months.

$$P(e_2) = \begin{cases} 0.4861 & June, July \\ & August, September \\ 0.1485 & otherwise \end{cases}$$

Scenario 3: Two peaks in the year, more than three months apart.

$$P(e_3) = \begin{cases} 0.1652 & March, June \\ 0.0659 & otherwise \end{cases}$$

For each of the scenarios total sample sizes $N = 10, 50, 500$ were employed. Along with the above scenarios the null data set was simulated for 365 days in order to estimate the critical value. The results of the power analysis are shown in the tables below.

In each of the tables the value shown is the probability of detecting a cluster. So given that 1000 simulations were performed the value represents the proportion of cases where a cluster was detected, given that the cluster was significant acoording to the critical value calculated for the null hypothesis. As the table shows proportions, any value with a power equal to one has a perfect cluster detection rate. A power score close to zero indicates poor power, and a high failure rate.

| | | | | N = 10 |
|---|---|---|---|---|
| | Binomial Scan | Poisson Scan | Circular Scan | Ratchet Scan |
| Scenario 1 | 0.18 | 0.18 | 0.18 | 0.60 |
| Scenario 2 | 0.32 | 0.32 | 0.32 | 0.70 |
| Scenario 3 | 0.15 | 0.15 | 0.15 | 0.60 |
| | | | | N = 50 |
| Scenario 1 | 0.71 | 0.46 | 0.71 | 0.75 |
| Scenario 2 | 0.91 | 0.79 | 0.91 | 0.91 |
| Scenario 3 | 0.51 | 0.23 | 0.51 | 0.74 |
| | | | | N = 500 |
| Scenario 1 | 1.00 | 1.00 | 1.00 | 1.00 |
| Scenario 2 | 1.00 | 1.00 | 1.00 | 1.00 |
| Scenario 3 | 1.00 | 1.00 | 1.00 | 1.00 |

Table 5.1: Power analysis of the scan statistics at $\alpha = 0.05$ significance

| | | | | N = 10 |
|---|---|---|---|---|
| | Binomial Scan | Poisson Scan | Circular Scan | Ratchet Scan |
| Scenario 1 | 0.18 | 0.01 | 0.18 | 0.60 |
| Scenario 2 | 0.32 | 0.07 | 0.32 | 0.70 |
| Scenario 3 | 0.15 | 0.01 | 0.15 | 0.60 |
| | | | | N = 50 |
| Scenario 1 | 0.71 | 0.13 | 0.46 | 0.52 |
| Scenario 2 | 0.91 | 0.53 | 0.79 | 0.79 |
| Scenario 3 | 0.51 | 0.03 | 0.23 | 0.17 |
| | | | | N = 500 |
| Scenario 1 | 1.00 | 1.00 | 1.00 | 1.00 |
| Scenario 2 | 1.00 | 1.00 | 1.00 | 1.00 |
| Scenario 3 | 1.00 | 1.00 | 1.00 | 1.00 |

Table 5.2: Power analysis of the scan statistics at $\alpha = 0.01$ significance

When $N$ is very small, the ratchet scan statistic appears to be the strongest of all the versions of scan. In each of the different scenarios, for $N = 10$ the ratchet scan statistic appears to be the most powerful, even at a significance level of $\alpha = 0.01$.

When $N = 50$ the scan methods seem to perform more equally, with the exception of the Poisson scan which performs poorly with all scenarios except scenario 2. The Binomial scan is equally powerful at $\alpha = 0.05$ and $\alpha = 0.01$. The Circular and ratchet scan statistic do not have the same capability at $\alpha = 0.01$. If $N$ is large, all the statistics have a perfect score of 1.

### 5.2.1 Conclusion

Based on this power analysis the Binomial Scan statistic seems to be the most consistent of all the tools. However if $N$ is very small (equal to 10), aggregating the data to monthly totals and applying the ratchet scan statistic seems to be the best choice.

## 5.3 Relative Cluster Size Affect

An important consideration of this analysis is the power of the scan statistic. How big must a cluster be in order for the scan statistic to detect it? Looking at Tables 3.1 and 3.2 the % column gives the cluster size as a percentage of the total in each age group. In the case of the male suicide table, males aged 20-29 years were found to have a significant cluster. However looking at the percentages, the cluster for this groups represents the same proportion of the total as the cluster for the group of males aged less than 20 years. Indeed, looking at the female suicide

table the clusters here represent much higher proportions of the total number of suicides in each group. Could it be that a smaller total size is less powerful at detecting a cluster? What size of cluster would be required in order for the scan statistic to be significiant?

Using the Binomial Scan statistic, the power of the scan statistic to detect a cluster was assessed for different values of the total size $N$. The values of $N$ chosen ranged from 10 to 200, to reflect a broad spectrum of sample sizes. Using arbitrarily selected cluster sizes, $n$, the level at which the scan statistic detect a cluster was calculated. Figure 5.1 shows the results of this analysis; the smaller values of $N$ require that the cluster be a high proportion of the total sample size, whereas for larger $N$ relatively smaller clusters can be detected. From the graph, the scan statistic appears to lose power at smaller $N$. When $N = 10$ a cluster will only be detected if it is at least approximately $55\%$ of the total; when $N = 200$ a cluster that is only $20\%$ of the total will be detected by the scan statistic.

### 5.3.1 Conclusion of Relative Cluster Size

Based on this analysis of the relationship between cluster size, total size ($N$) and significance we can conclude that if a sample is very large then a cluster that is perhaps only $20\%$ of the total size will be significant.

However if the total sample size is small, less than 10, then an apparent cluster of less than $20\%$ of the total will not be a significant cluster. In order for a cluster to be significant the cluster must represent at least $60\%$ of the total number of cases in the study.

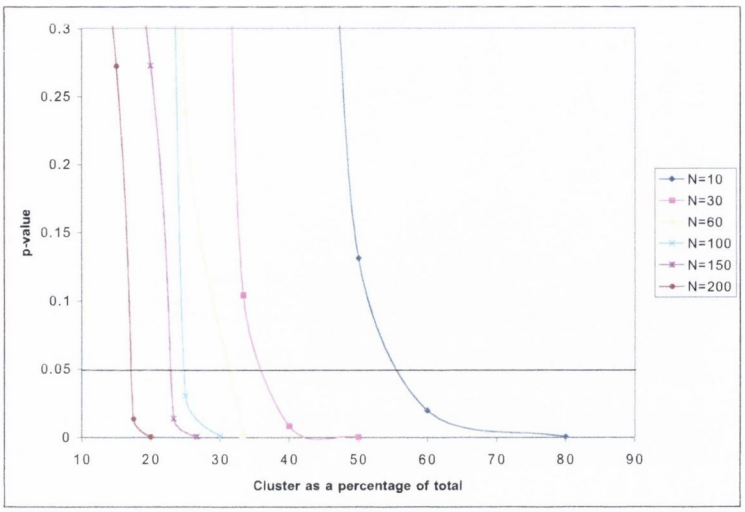


Figure 5.1: Power of the Scan Statistic to Detect different Cluster Sizes.

## 5.4 Overall Conclusion of Power Analysis

Within this chapter, three separate analysis were carried out. Each analysis was assessing some form of the 'power' of the scan statistic. If data are available on a daily basis it is best to analyse the data in this format, unless the data are quite seasonal then aggregating it and applying the ratchet scans statistic would be more successful than fitting a model to the daily data.

The binomial scan statistic would appear to be the best of all the versions of the scan statistic examined in this thesis. Not only is it the simplest of all the methods to apply, but if the numbers are large then it is the most efficient at detecting clusters.

The other element to impact on the use of the scan statistic is the relative size of the cluster compared to the overall size of the study. For a very large study then a cluster need only represent 20% of the total sample size to be significant.

However when the sample size is smaller (say $\leq 10$) then the cluster will need to be a much larger percentage of the total ($\geq 60\%$).

# Chapter 6

# Discussion and Conclusions

## 6.1 Important findings and original aspects of the work

The aim of the study was to assess the scan statistic as a suitable monitoring tool in health impact assessment. Monitoring tools have not been implemented in HIAs to date, so an important aspect of this research was to investigate the possibility of monitoring in the context of a HIA. Although the scan statistic has been suggested as an appropriate monitoring tool it had not been utilized or tested rigorously in practice.

### 6.1.1 Monitoring in Health Impact Assessment

#### Suicide

Clustering of suicides was found using the scan statistic. The scan statistic was found to be an important tool in retrospectively analyzing the data, although there

was no additional information to suggest what caused the cluster of suicides. A report was recently written about suicide among young males in Ireland [110]. This report suggested that the suicides were being caused by an increase in alcohol consumption. This report was published in 2004. Had a monitoring tool been in place, such as that in section 3.1, the increase would have been detected earlier, hence earlier provisions made to deal with the problem. As it is the problem has been identified and it is only now that solutions are being discussed, nearly 10 years later.

An important aspect of this section was the identification of a cluster of suicides by hanging. This is an important finding as there has been no published evidence of copycat suicides in Ireland to date. While this cluster alone is not definitive evidence of copycat suicides, it is enough warrant further exploration of the data and discussion of the possibility of copycat suicides in Ireland.

**Incinerator Example**

There is public concern about incinerators and their impact on health, and there is contradictory evidence to suggest that modern incinerators emit such small amounts of dioxins into the atmosphere that there is no threat to health. The incinerator proposed for Ringaskiddy is a modern design; planning permission has been granted with construction set to begin in January 2007. There is no evidence to suggest that long-term exposure to even small amounts of dioxin is safe. For this reason suspected health factors should be monitored as outlined on in section 3.3. This is easy to implement and it means that any negative impacts will be identified quickly, rather than waiting for a large, perhaps noticeable cluster to occur with undesirable public health consequences. Using the monitoring tool

it was possible to predict that any increase in lung cancer will be detected early enough to ensure that appropriate safety measures are put in place.

**Tram Example**

There was no HIA carried out on a new tram in Houston, Texas. As a tram is a new road user, people have to adjust to travelling in the city in new ways, and they need to become accustomed to sharing the road with a large, silent train. The Houston tram has developed a bad reputation for accidents and it is now known as the 'Wham-Bam Tram', if there had been a constant monitoring of accidents, appropriate safety measures could have been put in place before a bad reputation was earned. The continuing increasing accident rate in Houston could have been halted, ensuring a safer road for all users.

In this example the benefit of a monitoring system is clear. Had this monitoring system been in place for the Houston tram it is quite likely that better safety measures would have been put in place sooner. If there is no monitoring system there is no cut off period to help individuals decide when there has been one too many accidents.

**Smokey Coal**

There were issues with the introduction of the ban on bituminous coal, and the Fuel Trade Group was opposed to the ban. By monitoring the number of respiratory deaths a definite decrease in respiratory deaths was observed quickly. Once the evidence of the benefits is there, it would be unethical not to enforce the ban in the rest of the country.

#### Penalty Points

Penalty points were hailed as the answer to the carnage on the roads. By monitoring road fatalities a decrease post implementation of the ban was observed, which showed that the penalty points did save lives. However, further monitoring has shown that the death toll on the roads has risen again. Now two years after the penalty point introduction people are realising that penalty points are not working. Using the monitoring method this would have been established in a shorter time frame, and perhaps more checkpoints could have been introduced.

### 6.1.2 Scan Statistic as a Monitoring Tool

The scan statistic has not been used elsewhere to any great extent as a monitoring tool. The five examples where it has been applied as a monitoring tool in this thesis were all very different. In some cases the scan statistic was required to detect clustering of events; in other cases a drop in the number of events was more important. In each case the scan statistic was proved to be adaptable and could be applied with little effort. So how did the scan statistic cope as a monitoring tool?

#### The Scan Statistic Looking at Suicide Data

In the case of the suicide data, the use of the scan statistic was fairly straightforward. The binomial and circular scan statistic were employed to test for clustering retrospectively. Using the Poisson scan statistic enabled the establishment of a monitoring chart, and the Poisson scan gave a critical value that allowed the setting up of a critical line on a control chart. If the number of suicides in a particular time frame exceeded the critical line then it indicated a cluster of suicides.

The suicide data were aggregated to a monthly level to examine the possibility that the ratchet scan statistic would be more informative. It was found that the suspected cluster still proved significant and no information was lost by aggregating the data. However, by using the Binomial scan statistic on the daily data the exact time of the cluster could be identified.

**Using the Poisson scan statistic to monitor events**

**Incinerator data** In the case of the incinerator proposed for Ringaskiddy, a prospective situation, the incinerator is proposed and there is no data on cancer incidence in close proximity to the incinerator. However, using evidence from previous studies, the relative risk of cancer around an incinerator could be established. As the cancer rate in Co. Cork was known the expected cancer rate in Ringaskiddy could be estimated. As there was no information available on the total number of cancer cases the Poisson scan statistic had to be used. Using the relative risk of cancer around an incinerator, a Poisson scan critical value was computed and a monitoring chart set up. In order to check the monitoring chart, data were simulated, using a nonhomogeneous Poisson process, to approximate what the real life cancer rate would be if the incinerator resulted in the claimed increase in cancer.

The scan statistic could be adapted to cope with the rare events in this example. By using a longer scanning window of 6 months or more a monitoring chart could be set-up that functioned properly.

**Tramline data** Tramlines differ greatly, and an important factor in the expected number of incidents for a tram is the amount of shared road. Monitoring a new

tramline for accidents is a prospective or concurrent health impact assessment. As the tram has not been operating, there are no data available on the expected number of incidents. In the case of the tram in Houston Texas, a similar tram line with the same distance of on road use as Houston was used to establish the expected number of incidents. With this information a monitoring chart with Poisson critical limits was established and was effective at detecting an increase in tram incidents.

In many of the cases where daily data were available the Poisson scan statistic could be used to establish critical limits for a monitoring chart. The monitoring chart developed using the Poisson critical limits functioned very well in all of the examples cited above.

### 6.1.3 The scan statistic adjusted to monitor for expected dips

**Penalty point data** The penalty point data were the only data that were aggregated to a monthly level, which meant that the ratchet scan statistic had to be used. Another problem with these data was monitoring for a dip in events rather than a cluster. To monitor for a dip in events the ratchet scan statistic was adjusted, and new graphs were created to estimate p-values of significance. Using the adjusted ratchet scan statistic, a monitoring chart was set up and successfully monitored the road death data.

In cases where data were only available on a monthly basis the ratchet scan statistic still performed well as a monitoring tool, the only draw back being that the every month a new ratchet scan statistic had to be calculated and then a critical value computed.

**Smokey coal example - coping with seasonality in the scan statistic** The smokey coal ban provided the most problems for the scan statistic. The data for respiratory deaths were very seasonal, and an assumption of the scan statistic is that there is a constant population at risk. To use the scan statistic here, the seasonality had to be resolved. A number of different methods were used to cope with the seasonal trend. The most straightforward method is probably to deseasonalise the data. However this can be time consuming. There are a couple of other strategies that involve the estimation of an appropriate model.

Using Kulldorfs method the data were first modelled and then the model was used to create simulations, and then a critical value was estimated. This method requires an accurate model, and a knowledge of simulations, as for each new data set a new model would need to be derived and simulated. While the method may be effective with an accurate model getting a model accurate enough would be near impossible. The need for an accurate model is very limiting especially when dealing with data that is rarely predictable or compliant enough to be modelled.

Even though the respiratory death data were available on a daily basis, when aggregated to a monthly level the scan statistic performed more reliably. This is possibly because at a daily level there is a lot of day to day variation and fitting an accurate model in this circumstance is difficult. At a monthly level the fitting of a more accurate model is easier. Calculating deseasonalised data are also less time consuming. At a monthly level the ratchet scan statistic can be used to scan the data for dips. Another advantage of aggregating to a monthly level in this case is that a model does not need to be fitted and then simulated; the deseasonalised data can be scanned using the ratchet scan statistic.

### 6.1.4 Which of the scan statistics performs best?

To investigate which of the scan statistic methods performed optimally a power analysis was undertaken in Chapter 5 (section 5.2). The binomial, circular, Poisson and ratchet scan statistics have never been compared to each other. If there is the option of using any of the scan statistics, which one should be chosen?

The power analysis showed that, generally, under all the scenarios the binomial scan statistic performed best and was most likely to detect a real cluster.

## 6.2 Limitations

The scan statistic coped with the various tasks considered in this thesis. The only limitation was that when the data were highly seasonal, such as in the case of the respiratory deaths for the smokey coal example, the scan statistic could not be implemented directly in such an instance. However adjustments can be made to deseasonalise the data and then proceed as normal.

Another limitation may be that an increasing trend in the data may not be detected. However, trends can be accommodated by using Kulldorfs method outlined in section 4.1.3. If a trend is very slight then monitoring over short time period may also overcome this problem. Trends can be removed from data using time series methods.

The biggest limitation in monitoring health events in a HIA or using the scan statistic is the quality of data. The limitations already discussed here raise different data problems, but overall the quality of data are very important for the accurate monitoring of health events. Unfortunately when dealing with any type of health data the quality of data is not going to be optimal. However, as long as

the limitations of the data are known then they can be addressed to some extent, this was addressed in chapters 3 and 4.

## 6.3 Recent Developments in Scan

### 6.3.1 Syndromic Surveillance

Syndromic surveillance is a topic of much interest at the present time. The scan statistic is being examined for its benefits in syndromic surveillance. The scan is being examined with regard to improving its window monitoring shape so that monitoring along a particular street or river could be incorporated. This would not be possible currently due to the restrictions of the circular or square windows.

### 6.3.2 Tree Method

A presentation by Kulldorff [111] outlined possible benefits of a tree-based scan statistic. This method could be used to look at whether certain occupations are more at risk to certain diseases. The method involves scanning a tree and considering all possible cuts on any branch. The likelihood for each cut is calculated, and the cut with the maximum likelihood is the most likely cluster.

## 6.4 Further Work

This thesis has outlined the use of the temporal scan statistic as a monitoring tool in health impact assessment. In some cases a spatial element to the monitoring process is required. The next stage in this work should be to investigate the incor-

poration of spatial elements into HIA monitoring. The temporal scan statistic has been shown to be flexible and adaptable - it was applied to five different situations. However the spatial scan has not been applied as a monitoring tool in a HIA, and testing of the spatial scan statistic needs to be done so that spatial elements can be incorporated into a HIA. It would be interesting to compare the performance of the spatial and temporal scan statistics in these circumstances. The spatial scan statistic will add extra information to some of the situations that have been discussed. For example in the case of road fatalities are there areas of the country that are benefiting from introduction of penalty points? Are there certain roads where the number of accidents has dropped - perhaps these are roads where there are speed cameras.

The quantitative monitoring of HIA has been shown to be an important component of HIAs. Individuals using a HIA framework should not ignore this vital step. The benefits have been indicated in the examples explained in this work, and now it is time to ensure that the method is utilized.

An important step in ensuring the use of the scan statistic as a public health monitoring tool and the use of monitoring tools in HIA is publication and dissemination of the lessons learnt here. While some of the results presented here have been presented at HIA and public health conferences, presenting the results of the case studies at smaller public health conferences could have double benefits. The case studies are of general interest to people working in public health, and the scan statistic methodology used in each case would also be disseminated. This would enable the concept of public health surveillance to flow throughout the health boards.

A vital aspect of the development of the scan statistic is the development of

tools to enable its use. For a monitoring tools to be successful, automated monitoring of health events is needed. In an ideal set up, an automated monitoring system would inform the appropriate health official, by e-mail, of an out of control chart. With a set-up like this there would be little restriction on the number of monitoring charts in operation.

Further work needs to be done in developing quantitative tools for health impact assessment, while this thesis has focused on the monitoring stage, the other stages of the HIA process do require quantitative attention.

## 6.5 Conclusion

This thesis has shown the efficiency and the practicality of the use of the scan statistic in health impact assessments. While the general focus has been on the application as a monitoring tool, the benefits of using the scan statistic to scan for clusters retrospectively has been highlighted.

The temporal scan statistic had not been tested or used as monitoring tool, the examples used in this thesis rigourously tested the scan statistic and showed it to be an effective public health monitoring tool.

We have shown that there is evidence of clustering in suicides in Ireland, particularly amongst young men. The scan statistic was useful in the detection of a cluster of suspected copycat suicides. Even when the health impact assessment is prospective, as was the case with the Ringaskiddy incinerator and the Houston tramline, it is still possible to use the scan statistic to support an effective monitoring system.

The emphasis in a health impact assessment is to reduce negative health im-

pacts. However it is also important to monitor positive health impacts to ensure that the expected benefits will not be short-lived. In monitoring the respiratory data post implementation of the bituminous coal ban, a definite benefit was observed: there was a decrease in respiratory deaths. Monitoring road fatalities post implementation of penalty points showed a short-lived benefit and it also highlighted the failure of the introduction of further penalty points for dangerous driving and no seatbelts.

A power analysis of the temporal scan statistic had not been carried out prior to the completion of this thesis. The power analysis completed in chapter 5 not only illustrated what happened when only aggregated data were available but it compared the various versions of the scan statistic under different conditions, such as with different total sizes and different possible cluster types. This chapter also demonstrated the effect that the total sample size has on whether a cluster will be significant or not.

For ease of application and accuracy the binomial scan statistic was found to be the preferable version of the scan statistic. It is the easiest of all the methods to apply and so it should appeal to those without sophisticated statistical packages. It was also highly accurate at detecting clusters in the power analysis chapter. However, it did lose some power for very rare events and in such situations the data should be aggregated and the ratchet scan statistic should be used.

The wide range of topics that have been illustrated in this thesis demonstrate not only the flexibly of health impact assessment but also the adaptability of the scan statistic to any situation. This makes the scan statistic ideal for implementation in a health impact assessment environment.

# Appendix A

# Health Impact Assessment Tools

## A.1 The Swedish Model

The Swedish model [15] developed for health impact assessment focuses on assessing the impacts of those suffering from health inequalities. This tool measures the impact of polices on minority groups, and a policy may be seen as more favourable if it has more beneficial health impacts for a marginalised group. A key question asked in the health impact analysis is: "How is the health of different groups affected by the proposed policy decision in question?"

In the Swedish model for health impact analysis there are three tools utilized, 'the health question', 'the health matrix' and 'health impact analysis'. Depending on the complexities of the proposed decision the most appropriate instrument can be applied.

'The health question' [15] can be used as a policy audit tool or as a screening tool and a starting point for scoping. It consists of a list of health impacts (see Figure A.1), the use of which is supported by the following key determinants of

health:

1. democracy/opportunity to exert influence/equality,
2. financial security,
3. employment/meaningful pursuits/education,
4. social network,
5. access to health care and welfare services,
6. belief in the future/life goals and meaning,
7. physical environment and
8. Living habits.

'The health matrix' [15] helps to identify the consequences of a policy proposal on the health determinants listed above. Health impacts are judged and marked according to their severity by one or more pluses or minuses in the table shown in Figure A.1, a '0' is used to indicate no impact.

Health impact analysis asks key questions that provide a foundation for health impact assessment prior to decision making. There are seven questions (as in Figure A.1) and they serve as a useful checklist to ensure that everything has been addressed and all options considered in the course of the health impact analysis.

## A.2 The Ten-Step Model

In Bielefeld, Germany a ten-step model [17] was developed for environmental health impact assessment. The model is shown in Figure A.4. Project analysis is

**The Health Question**

This simple option can be adopted prior to consideration of an individual policy proposal. It can also be used before collective decisions are made at meetings of local boards/committees.

Will the proposal promote health development for various groups/the population in relation to the social environment (e.g. opportunity to exert influence, mutual work and support)?

Yes ○ No ○

Will the proposal promote health development for various groups/the population with regard to certain risk factors (e.g. the physical environment or living habits)?

Yes ○ No ○

Is the proposal consistent with overall municipality/county health targets and objectives?

Yes ○ No ○

Comments/justification:

Alternative proposal:

Our assessment is that:

Figure A.1: The Health Question

**The Health Matrix**

| | Prioritized group | | Entire population | |
|---|---|---|---|---|
| | Long term | Short term | Long term | Short term |
| Democracy/opportunity to exert influence/equality | | | | |
| Financial security | | | | |
| Employment/meaningful pursuits/education | | | | |
| Social network | | | | |
| Access to health care and welfare services | | | | |
| Belief in the future/life goals and meaning | | | | |
| Physical environment | | | | |
| Living habits | | | | |

Is the proposal in accordance with the overall targets of the municipality/county council?
Yes ☐ No ☐

Comments/justification:

Alternative proposal:

Our assessment is that:

Figure A.2: The Health Matrix

**Health Impact Analysis**

Health Impact analysis is guided by a number of key questions. They may, for example, be appropriate to raise prior to analyses of strategic policy decisions.

**General questions**

1a. What does the local Public Health Report show regarding the health conditions of different groups within the municipality/county? Are there groups which are particularly vulnerable or already exposed to numerous health risks, or are there groups with evident health-trend problems?

1b. Are there defined health-policy targets?

**Questions linked to the matter at hand**

2. Are there particular health risks which can be expected to decrease or increase as a result of the proposal? Will impacts become apparent in the short term (within 5 years) or in the long term.

3. For the distribution of ill-health within a population, it is of decisive importance which groups are subjected to decreased/increased health risks, and whether any decision will affect these groups' capacity either to deal with difficulties or, by contrast, increase their vulnerability.

4. In what way will the social environment in the local community be affected by the proposal?

5. Is there a risk that a proposal may have a "double" impact on certain groups. I.e. that both their health risks increase and their social environment deteriorates?

6. Are there alternative policies which might result in better health for exposed groups and the population as a whole?

7. Summary

Figure A.3: The Health Matrix

obviously an inquiry of whatever project or policy is to be assessed, independently of the project analysis a regional and population analysis are carried out. Regional analysis refers to the physiogeography, meteorology, natural features and land use, the environmental aspect of the analysis can be seen clearly here. Population analysis describes the general demography, the health status and the behavioural patterns.

Combining the regional analysis and the project analysis, predictions about future pollution is made and this information is then combined with any background knowledge and the population information to predict the health impact. Recommendations and evaluations can then be made based on the investigation.

The ten-step model was applied to the enlargement of an existing waste disposal facility in Lower Saxony. The model was also applied to a planned new highway. Each case included the analysis of alternative options, in the waste disposal case the alternative being no extension, and in the highway situation alternative locations were assessed. In both of these field applications it was found that the ten-step model was a success, local health departments that were involved had positive responses about it, and it was subsequently formally approved by the German Conference of State Health Ministers.

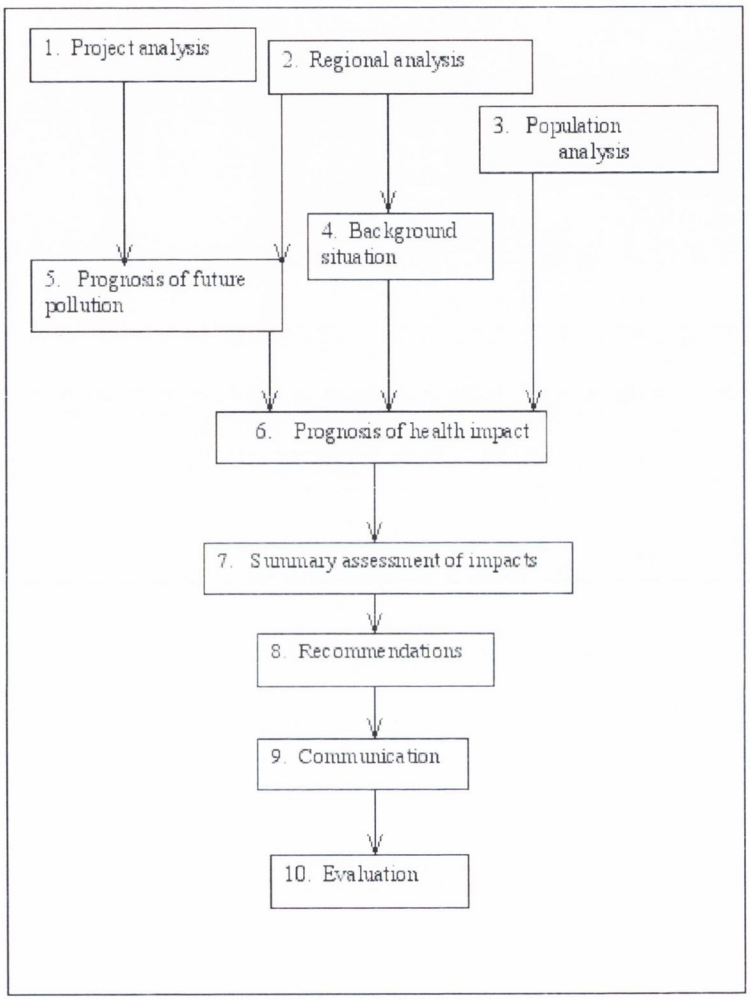


Figure A.4: The Health Matrix

# Appendix B

# Algorithms & Programs

## B.1 Simulation of Non-Homogenous Poisson Process

The non-homogenous Poisson process (NHPP) can be simply explained as being a Poisson process with a variable intensity defined by the deterministic intensity function $\lambda(t)$, where $t$ is time and $\lambda$ is the rate of occurence, in other words the rate varies over time. The Poisson process assumes stationary increments, the nonhomogeneous Poisson process relaxes that assumption so the arrival rate need not be constant but it can vary with time. A NHPP can model situations where event occurrence is subject to changes due to seasonality or trends. Hence it will be useful to simulate different possible scenarios that could occur due to the presence of an incinerator.

Simulation of the different scenarios using non-homogenous Poisson Process was done in VBA for Excel; the code is based on an algorithm developed by Ross [112]. The method used to simulate the NHPP is known as the thinning or rejection method. The steps of the algorithm as outlined by Ross [112] for the

thinning method applied over each subinterval are given below, where $t$ represents the present time, $J$ the present interval, $I$ the number of events so far and $S(1)$, ..., $S(I)$ the event times. The algorithm was implemented using VBA for Excel, and the code is given in Appendix B.2.

**Step 1** $t = 0$, $J = 1$, $I = 0$.

**Step 2** Generate a random number $U$ and set $X = \frac{-1}{\lambda_J} \log(U)$

**Step 3** If $t + X > t_J$, go to **Step 8**.

**Step 4** $t = t + X$

**Step 5** Generate a random number $U$

**Step 6** If $U \leq \frac{\lambda(t)}{\lambda_J}$, set $I = I + 1$

**Step 7** Go to **Step 2**

**Step 8** If $J = k + 1$, stop.

**Step 9** $X = (X - t_J + t)\lambda_J \lambda_{J+1}$, $t = t_J$, $J = J + 1$

**Step 10** Go to **Step 3**

## B.2 VBA Excel Programs

The following program, written in VBA Excel, was used to simulate the non-homogeneous Poisson process.

```
Option Explicit
Public Function lambdat(tPresTime)
If 0 <= tPresTime And tPresTime < 731 Then
lambdat = 2.8411
```

```
        + 1.0864 * Cos((2 * (22 / 7) / 365.25) * tPresTime)
        + 0.6949 * Sin((2 * (22 / 7) / 365.25) * tPresTime)
Else: lambdat = 100
End If
End Function
Public Function lambdaj(jPresInt)
If 0 <= jPresInt And jPresInt < 731 Then
lambdaj = 2.8411
        + 1.0864 * Cos((2 * (22 / 7) / 365.25) * jPresInt)
        + 0.6949 * Sin((2 * (22 / 7) / 365.25) * jPresInt)
Else: lambdaj = 100
End If
End Function
Public Function StepTwoX(lambdaj)
StepTwoX = (-1 / lambdaj) * Log(Rnd)
End Function
Sub MixedPoissonProcess()
   Static tPresTime, jPresInt, INumEvnts, EventTime, S
   S = 0
   tPresTime = 0
   jPresInt = 1
   INumEvnts = 0
   Dim X
   Do
    X = StepTwoX(lambdaj(jPresInt))
```

```
    If tPresTime + X > jPresInt Then
   X = (StepTwoX(lambdaj(jPresInt)) - jPresInt + tPresTime)
      * lambdaj(jPresInt) * lambdaj(jPresInt + 1)
                    tPresTime = jPresInt
                    jPresInt = jPresInt + 1
 Else
    tPresTime = tPresTime + X
  If Rnd <= lambdat(tPresTime) / lambdaj(jPresInt)
  Then
          INumEvnts = INumEvnts + 1
            S = tPresTime
            End If
       With Worksheets("Sheet1").Range("a1")
      .Offset(INumEvnts, 0) = INumEvnts
     End With
    End If
   Loop Until tPresTime = 731
End Sub
```

## B.3 Mathematica Programs

The following programs are available from Dr. Alan Kelly, SAHRU, for the calculation of the various scan statistics outlined in Chapter 2.

### B.3.1 Poisson Scan Statistic

```
Needs["Statistics`DiscreteDistributions`"]


fp[x_,psi_]:=NSum[PDF[PoissonDistribution[psi],i],{i,0,x}]


poisPDF[x_,psi_]:=PDF[PoissonDistribution[psi],x]


a1[x_,psi_]:=
      2*poisPDF[x,psi]*fp[x-1,psi]*((x-1)*fp[x-2,psi]
      -(psi*fp[x-3,psi]))


a2[x_,psi_]:=
        (0.5*(poisPDF[x,psi])^2)
            *(((x-1)*(x-2)*(fp[x-3,psi]))
             -((2*(x-2)*psi*fp[x-4,psi])
             +(psi*psi*fp[x-5,psi])))


a3[x_,psi_]:=NSum[(poisPDF[2*x-r,psi])
             *(fp[r-1,psi]^2),{r,1,x-1}]
```

```
a4[x_,psi_]:=
  NSum[(poisPDF[2*x-r,psi]*
          poisPDF[r,psi])*(((r-1)*fp[r-2,psi])
          -(psi*fp[r-3,psi])),{r,2,x-1}]
q2star[x_,
    psi_]:=(fp[x-1,psi]^2)-((x-1)
             *poisPDF[x,psi]*poisPDF[x-2,psi])
           -((x-1-psi)*poisPDF[x,psi]*fp[x-3,psi])

q3star[x_,psi_,a1_,a2_,a3_,a4_]:=(fp[x-1,psi]^3)
                                  -a1+a2+a3-a4

q4star[x_,psi_,l_,q3star_,q2star_]:=(q3star/q2star)^l

poiscan[k_,psiL_,linv_]:=
  Module[{p,aone,atwo,athree,afour,qtwo,qthree,qfour,psi,l},
                  l=1/linv;
    psi=psiL/l;x=k;Print["Number of cases= ",k];
    Print["Average number of cases expected= ",N[psi]];
    Print["Period length= ",l];
    aone=a1[x,psi];Print["a1= ",aone];
    atwo=a2[x,psi];Print["a2= ",atwo];
    athree=a3[x,psi];Print["a3= ",athree];
    afour=a4[x,psi];Print["a4= ",afour];
    qtwo=q2star[x,psi];Print["q2= ",qtwo];
```

```
qthree=q3star[x,psi,aone,atwo,athree,afour];
Print["q3= ",qthree];
qfour=q4star[x,psi,l,qthree,qtwo];Print["q4= ",qfour]]
```

### B.3.2 Binomial Scan Statistic

```
Needs["Statistics`DiscreteDistributions`"];
binscan[x_, y_, z_] :=
  Module[{w, n, k, bindist, cdist, p}, k = x; n = y; w = z;
    bindist = PDF[BinomialDistribution[n, w], k];
    cdist = 1 - CDF[BinomialDistribution[n, w], k - 1];
    p = ((k*(1/w) - (n - 1))*bindist) + (2*cdist); Print[p]]
```

### B.3.3 Ratchet Scan - Linear

```
<< Statistics`DiscreteDistributions`;
<< Statistics`MultiDiscreteDistributions`
fractmonth =
{31, 28, 31, 30, 31, 30, 31, 31, 30, 31, 30, 31}/365.
NB For m < c - 1and c  2 m
binpdf[x1_, n1_, p1_] :=
N[PDF[BinomialDistribution[n1, p1], x1]];
bintail[x2_, n2_, p2_] :=
N[1 - CDF[BinomialDistribution[n2, p2], x2]
                    + binpdf[x2, n2, p2]];
trinom[s3_, n3_, p3_, q3_] :=
```

$$N[\sum_{i=s3}^{n3-s3}\sum_{j=s3}^{n3-i}\frac{n3!}{i!j!(n3-i-j)!}(p3)^i(q3)^j(1-(p3)-(q3))^{n3-i-j}]$$

```
ratlingen[window_, size_, xval_, totval_, period_List] :=
  Module[{m = window, c = size, x = xval, n = totval,
  f = period, r, s, s1, s2, qij},
    Print[m, "   ", c, "   ", x, "   ", n];
    Do[qij[i, j] = 0 , {i, 1, c}, {j, 1, c}];
```

$$Do[qij[i,j] = trinom\left[x, n, \sum_{s=i}^{i+m-1} f[[s]], \sum_{s=j}^{j+m-1} f[[s]]\right],$$
$$\{i, 1, c-2m+1\}, \{j, i+m, c-m+1\}];$$

$$Do[$$
$$qij[i, i+u] = Sum[binpdf\left[s, n, \sum_{r=i+u}^{i+m-1} f[[r]]\right]$$
$$trinom\left[x-s, n-s, \frac{\sum_{r=i}^{i+u-1} f[[r]]}{1-\sum_{r=i+u}^{i+m-1} f[[r]]}, \frac{\sum_{r=i+m}^{i+m+u-1} f[[r]]}{1-\sum_{r=i+u}^{i+m-1} f[[r]]}\right],$$

$\{s, 0, x-1\}] + bintail\left[x, n, \sum_{r=i+u}^{i+m-1} f[[r]]\right], \{u, 1, m-1\},$
$\{i, 1, c-m+1-u\}\Big];$
$s1 = Sum[bintail[x, n, \sum_{r=i}^{i+m-1} f[[r]]\Big], \{i, 1, c-m+1\}\Big];$

```
s2 = Sum[qij[i, j], {j, 2, c - m + 1}, {i, 1, j - 1}];
  upr = Min[1,
      s1 - Max[Table[Sum[qij[i, j],
      {i, 1, j - 1}], {j, 1, c - m + 1}]]];
  Print["Upper bound = ", upr];
  k = 1 + Floor[2 s2/s1];
  lwr = 2 (k s1 - s2)/(k (k + 1));
  Print["Lower bound = ", lwr]
  ]
```

### B.3.4 Ratchet Scan - Circular

```
<< Statistics`DiscreteDistributions`;
<< Statistics`MultiDiscreteDistributions`
fractmonth =
{31, 28, 31, 30, 31, 30, 31, 31, 30, 31, 30, 31}/365.
NB For m < c - 1and c  2 m
binpdf[x1_, n1_, p1_] :=
N[PDF[BinomialDistribution[n1, p1], x1]];
bintail[x2_, n2_, p2_] :=
N[1 - CDF[BinomialDistribution[n2, p2], x2]
                    + binpdf[x2, n2, p2]];
trinom[s3_, n3_, p3_, q3_] :=
```

$N[\sum_{i=s3}^{n3-s3} \sum_{j=s3}^{n3-i} \frac{n3!}{i!j!(n3-i-j)!} (p3)^i (q3)^j (1-(p3)-(q3))^{n3-i-j}]$

```
mod2[z_, z_] = z; mod2[z_, y_] = Mod[z, y];
ratcircgen[window_, size_, xval_, totval_, period_List] :=
  Module[{m = window, c = size, x = xval, n = totval,
          f = period, r, r1, s1, s2, qij},
    Print[m, "   ", c, "   ", x, "   ", n];
    Do[qij[i, j] = 0 , {i, 1, c}, {j, 1, c}];
```

$Do[qij[i,j] = trinom\left[x, n, \sum_{s=i}^{i+m-1} f[[mod2[r,c]]], \sum_{s=j}^{j+m-1} f[[mod2[r,c]]]\right],$
$\{i, 1, c-m\}, \{j, i+m, Min[i+c-m, c]\}];$

Do[

$qij[i, i+u] = Sum[binpdf\left[s, n, \sum_{r=i+u}^{i+m-1} f[[mod2[r,c]]]\right]$

$$trinom\left[x-s, n-s, \frac{\sum_{r=i}^{i+u-1} f[[mod2[r,c]]]}{1-\sum_{r=i+u}^{i+m-1} f[[mod2[r,c]]]}, \frac{\sum_{r=i+m}^{i+m+u-1} f[[mod2[r,c]]]}{1-\sum_{r=i+u}^{i+m-1} f[[mod2[r,c]]]}\right],$$
$$\{s, 0, x-1\}] + bintail\left[x, n, \sum_{r=i+u}^{i+m-1} f[[mod2[r,c]]]\right], \{u, 1, m-1\},$$
$$\{i, 1, c-u\}\Big];$$
$$s1 = Sum[bintail[x, n, \sum_{r=i}^{i+m-1} f[[mod2[r,c]]]\Big], \{i, 1, c\}\Big];$$

```
s2 = Sum[qij[i, j], {j, 2, c}, {i, 1, j - 1}];
upr = Min[1, s1 - Max[Table[Sum[qij[i, j],
          {i, 1, j - 1}] - qij[j, j], {j, 1, c}]]];
  Print["Upper bound = ", upr];
  k = 1 + Floor[2 s2/s1];
  lwr = 2 (k s1 - s2)/(k (k + 1));
  Print["Lower bound = ", lwr]
  ]
```

# Appendix C

# Report on Excess Winter Mortality

The phenomenon of excess winter mortality is not a modern circumstance, as early as 1847 Farr [113] described the diagnostic composition of deaths in that year. That more people die during the winter period than any other time of the year is a well-documented fact, excess winter mortality has been studied in Italy [114], Europe [115], Norway and Ireland [116, 117].

It has been reported that poor housing conditions and fuel poverty are the main contributors to excess winter mortality. A study by Clinch and Healy [116] compared excess winter mortality in Ireland and Norway, it found that the excess was higher in Ireland due to the poorer housing conditions. Deprivation and rurality should be logical contributing factors to excess winter mortality. However a number of studies conducted in the United Kingdom have disproved this thinking [118, 119, 120]

## C.1 Methodologies

In Germany [121] mortality data were analysed for the period 1946-1995, it was found that the extent of excess winter mortality had declined, this was attributed to improvement in central heating of homes and an improved public health service. In Great Britain [122] it was shown that a lack of central heating in the home was associated with higher excess winter mortality.

A study conducted by the Eurowinter group [115] examined some contributing factors to excess winter mortality in European countries. The Eurowinter Group estimated the percentage increases in deaths per day per 1 °C fall in temperature below 18 °C, by generalised linear modelling. Cause specific data, such as high mean winter temperature, low living-room temperature and proportion of people wearing hats, scarves or gloves, from a number of European countries was analysed using multiple regression. It was found that percentage increases in mortality with fall in temperature were greater in countries with mild winters, these results concurred with the observation that protective measures against a given degree of cold were fewer in countries with mild winters. Individuals living in countries with mild climates do not dress for the weather.

Studies on excess winter mortality have been devised using a range of different methods. A report on winter mortality published by two statisticians at the Office of Population Censuses and Surveys made the following point. "There are various ways to divide the year so as to study patterns of seasonal mortality and in particular to define winter deaths"

In Sweden [123] a weighted regression analysis using second-degree polynomials was used to analyse the data. The regional variation in coronary mortality

and the relation to cold exposure in the 284 Swedish municipalities during a ten-year period was studied. One weather station in each municipality was chosen and the temperature recorded five times a day. A cold index was calculated as a logarithm of the number of times the temperature was recorded below a cut-off point in the ten-year period. Other data collected included social factors, butter sales, antihypertensive drug sales, smoking prevalence and drinking water parameters.

In Emilia-Romagna, Italy, mortality data from the year 1997 was analysed by Cordioli et al [114], specifically to look at mortality from ischaemic heart disease, hypertension, cerebrovascular and respiratory disease in 50-89 year-olds. Data were collected from the "Ufficio Risorse Informative" and "Servizio Meterologico". The number of deaths in the following age groups 50-59, 60-69, 70-79 and 80-89 was recorded for the following ICD codes: IHD 410.0-414.9; HY 401.0-405.9; CV 430.0-438.9, 490.0-493.9. Student's t test was used to analyse the data. It was found that cause-specific deaths were responsible for one third of all deaths and that they increased with age and cold in ER, the maximum number of deaths being in January.

Moran et al [124] examined excess winter mortality in Ireland. The relationship between meteorological conditions and seasonal morbidity and mortality patterns in the elderly ($> 65$ years) was examined over a four year period. Climate data were obtained from Met Eireann for four meteorological stations Dublin, Cork, Shannon and Clones. The first three stations were chosen because they are all near large population centres. Average monthly figures for temperature, rainfall, humidity and wind speed for 1994-1997 were calculated. Regional summer/winter temperature and mortality ratios were calculated using January and August data.

Healy and Clinch looked at housing standards and excess winter mortality in Ireland. They expressed winter as the period between December and March, and they compared these months with the non-winter months (between April and November). They found that excess winter mortality from cardiovascular disease was twice as high in Ireland as Norway [116].

## C.2 Methodologies Applied to Irish Data

Seasonal variation in mortality in Moscow [125] was examined by inspecting crude, smoothed, and deseasonalised trends. Auto-correlation functions were estimated and deaths were regressed against temperature. In order to estimate the excess winter mortality the additional deaths from October to March were compared to April to September and expressed as a percentage of the non-winter deaths. Using their method for calculating excess winter mortality, the Irish excess was calculated and is shown in table C.1.

| Winter period (Oct-Mar) | Respiratory | Circulatory | All Cause Mortality |
|---|---|---|---|
| 89 | 45.51 | 19.12 | 17.52 |
| 90 | 57.34 | 18.43 | 17.83 |
| 91 | 40.41 | 22.11 | 18.81 |
| 92 | 48.13 | 15.19 | 14.99 |
| 93 | 45.12 | 12.51 | 14.57 |

Table C.1: Excess winter mortality for Ireland, 1989-1993. Calculated using the Oct-Mar method.

Figure C.1 shows the months that were included as 'winter' months in the Moscow calculation, these months are represented by blue dots on the graph.

The graph illustrates that the months used were not always the highest mortality months for the year, there are many months with mortality counts higher than the stated 'winter' months.

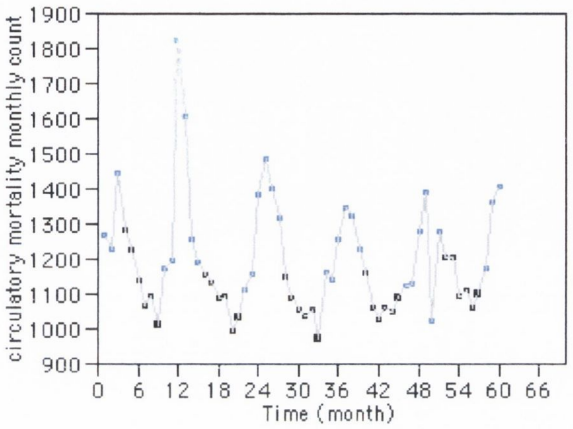


Figure C.1: Actual monthly mortality occurrence in Ireland 1989-1993.

In Finland [126], seasonal variation over time was examined by looking at the smoothed daily counts over a period of 35 years. To calculate the excess winter mortality the cold months, September to March, were compared to the month with lowest mortality. This method was applied to the Irish context. The results calculated using data from 1989-1993 are in table C.2. Using this method in the Irish situation means that the estimate of excess winter mortality could be weaker than the reality. The mortality rates seem to peak over 2-3 months, using a 7-month winter period means that the excess will appear smaller than the reality. Figure C.2 shows the monthly data for the period 1989-93; the mortality rates for months September to March are highlighted in blue. From the graph it seems that

the selected winter months are slightly imbalanced, there are many months not included in the winter calculation that have a higher mortality than months that have been included as winter months.

| Winter period (Sep-Mar) | Respiratory | Circulatory | All Cause Mortality |
|---|---|---|---|
| 89 | 70.71 | 22.74 | 20.58 |
| 90 | 79.43 | 25.36 | 22.38 |
| 91 | 71.24 | 20.33 | 21.14 |
| 92 | 54.93 | 18.50 | 18.00 |
| 93 | 62.97 | 17.65 | 16.74 |

Table C.2: Excess winter mortality for Ireland, 1989-1993. Calculated using the Näyhä method

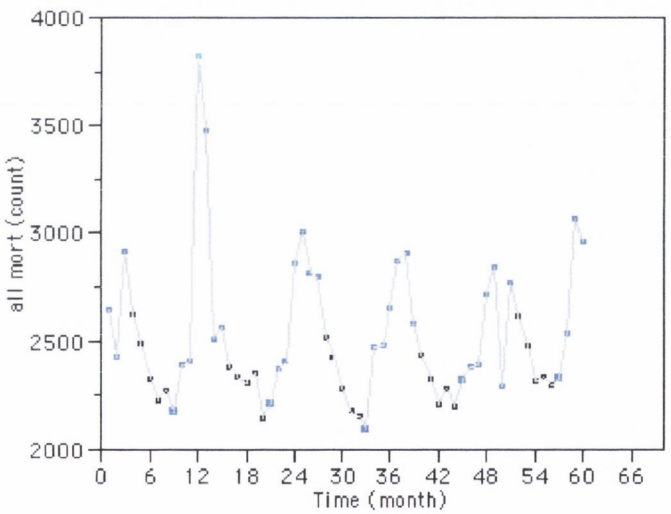


Figure C.2: Actual monthly mortality occurrence in Ireland 1989-1993.

Seasonal variations in Norway and Ireland [117] were compared; the excess

winter mortality was expressed as the difference between the August and January mortality values. This method makes the assumption the January will have the peak of mortalities and August will be the month of lowest mortality rate. The estimates are obtained using the Irish data, they are presented in Table C.3, and are very different from the estimates previously obtained. The percentage excess varies hugely from year to year, and while the respiratory mortality case is exceptional the excess differs by as much as 200% in some years.

| Winter period (Jan) | Respiratory | Circulatory | All Cause Mortality |
|---|---|---|---|
| 89 | 66.39 | 15.81 | 16.38 |
| 90 | 252.56 | 61.31 | 61.99 |
| 91 | 113.42 | 40.99 | 39.06 |
| 92 | 101.63 | 27.85 | 30.41 |
| 93 | 57.99 | 30.85 | 23.53 |

Table C.3: Excess winter mortality for Ireland, 1989-1993. Calculated using the Jan versus Aug method

Figure C.3 highlights the peak month and the trough month according to the method stated by Eng and Mercer [117]. Looking at the 5 year period, 1989-93, the peak in each year occurs in January (blue dot) three out of five times, the trough occurs in August (red dot) in just one of the years. This method does not seem appropriate to use in this situation.

The Office of National Statistics in the United Kingdom has published figures on the excess winter mortality for the years 1999-2002 [127, 128]. They define excess winter as deaths occurring in December-March minus the average of the deaths occurring in the proceeding August to November and the following April

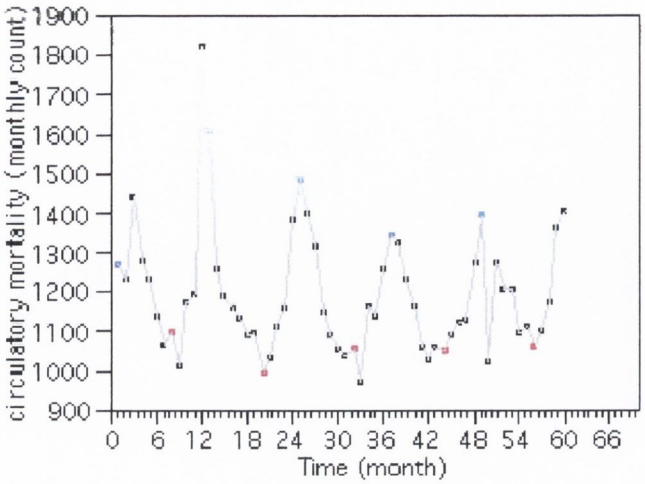


Figure C.3: Actual monthly mortality occurrence in Ireland 1989-1993.

to July. This method was applied to Irish data, the results obtained are shown in table C.4. This method uses a tighter definition of winter and so the excess winter mortality values are larger than previous estimates. It is apparent from the graph (Figure C.4 that this method has captured most of the peaks in the data. However, there was a peak in mortalities in November 1993, and while the excess for the winter of this period was not calculated, an estimate based on the Dec-Mar methodology would not pick up on that peak and so the excess would be underestimated.

A more sophisticated method for estimating excess winter mortality was employed in Bangladesh [129]; trigonometric models were fit to monthly data for the years 1982-1990. Using similar models the Irish data was examined. The first model fitted was a simple linear model, as can be expected this model did not approximate the data very well, it did not model for the seasonality of the data, a

| Winter period (Dec-Mar) | Respiratory | Circulatory | All Cause Mortality |
|---|---|---|---|
| 89/90 | 109.02 | 31.20 | 32.80 |
| 90/91 | 55.13 | 29.62 | 23.71 |
| 91/92 | 58.40 | 19.36 | 19.22 |
| 92/93 | 29.98 | 10.23 | 11.67 |

Table C.4: Excess winter mortality for Ireland, 1989-1993. Calculated using the Dec-Mar methodology.

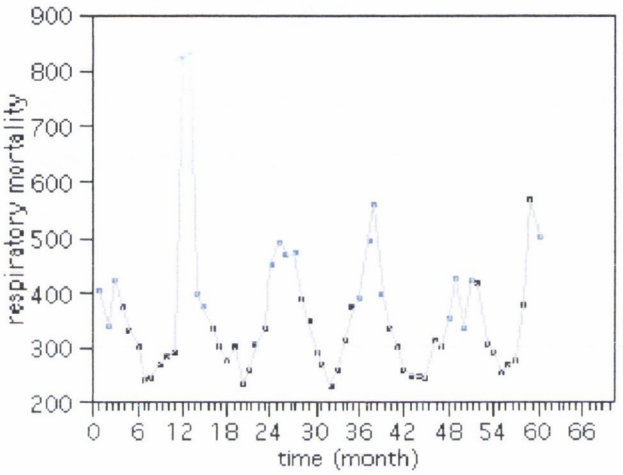


Figure C.4: Actual monthly mortality occurrence in Ireland 1989-1993.

similar result was found in the Bangladesh situation.

Model II used trigonometric techniques. Model II was devised using the fol-

lowing expression:

$$Y_t = \mu + \beta_0 t + \beta_1 x_{1t} + \beta_2 x_{2t} \tag{C.1}$$

$$\tag{C.2}$$

$$Y_t = \text{mortality at time (month) t} \tag{C.3}$$

$$x_{1t} = \cos(\frac{2\pi}{12}t) \tag{C.4}$$

$$x_{1t} = \sin(\frac{2\pi}{12}t) \tag{C.5}$$

Figure C.5 shows model II fitted to the circulatory mortality data, grouped by month for the years 1989-1993. The solid black line gives the estimated data. From the graph it can be seen that this model estimates the data with some accuracy, there are a number of outlier points that have not been predicted well. A similar situation occurred in the Bangladesh case and the model was adapted to account for a peak in the data.

To model for the unusual peak that occurred in the winter of 1989/1990 the following model was fitted, following the procedure used by Becker and Weng [129].

$$Y_t = \mu + \beta_0 t + \beta_1 x_{1t} + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} \tag{C.6}$$

where:

$$x_{1t} = \begin{cases} \cos(\frac{2\pi}{12}t) & if t < 12 and t > 13 \\ 0 & otherwise \end{cases}$$

$$x_{2t} = \begin{cases} \sin(\frac{2\pi}{12}t) & if t < 12 and t > 13 \\ 0 & otherwise \end{cases}$$

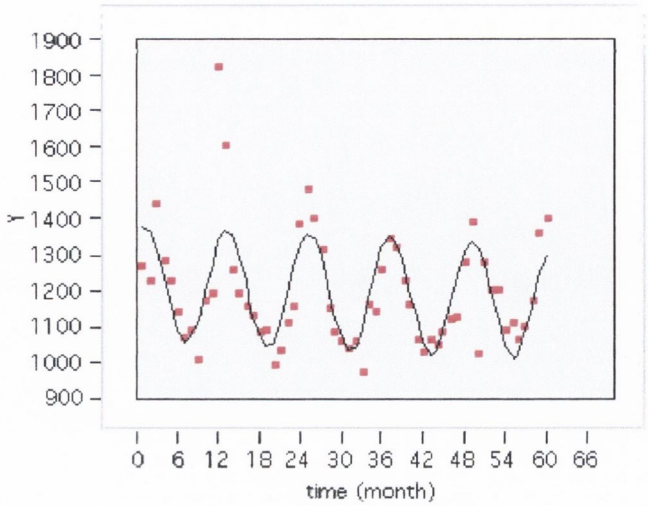


Figure C.5: Actual and predicted monthly circulatory mortality occurrence in Ireland 1989-1993 using Model II

$$x_{3t} = \begin{cases} 2\cos(\frac{2\pi}{12}t) & if 12 \leq t \leq 13 \\ 0 & otherwise \end{cases}$$

$$x_{4t} = \begin{cases} \sin(\frac{2\pi}{12}t) & if 12 \leq t \leq 13 \\ 0 & otherwise \end{cases}$$

Equation C.6 provides a much better fit of the data, as seen in figure C.6, the error of the model is also greatly reduced. Model III proved to be a better fit for the respiratory and all cause mortality data also as can be seen in figures C.7 and C.8. There are other winter periods in the 5-year period chosen that have not been predicted well, this is clear in the three graphs. The respiratory mortality data were estimated most accurately by model III, compared to the other two data sets,

it had the largest R-square value and the lowest error rate, and the graph of the respiratory data justifies this finding.

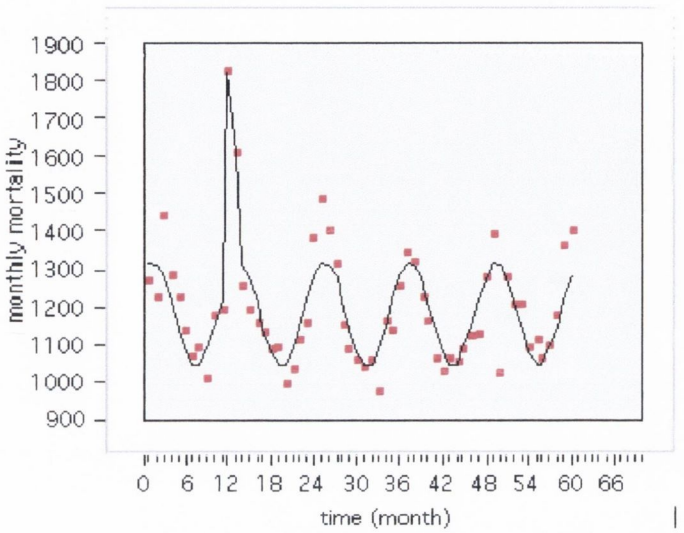


Figure C.6: Actual and predicted monthly circulatory mortality occurrence in Ireland 1989-1993 using equation C.6

To estimate the excess winter mortality the amplitude is calculated, this is equal to $\frac{\sqrt{\beta_1^2+\beta_2^2}}{\mu+30.5\beta_0}$ , where 30.5 is the midpoint of the time interval in months. The calculated excess winter mortality is a ratio of the mean number of deaths per month, the calculated value of the excess is shown in table'C.5. The excess winter mortality for respiratory diseases is over double the figures for circulatory and all cause mortality.

Another form of trigonometric modeling was adapted by Gemmell et al'[130]. The Poisson form of the generalized linear model was used, the offset term used the expected values, which were computed using simple linear model, and the log

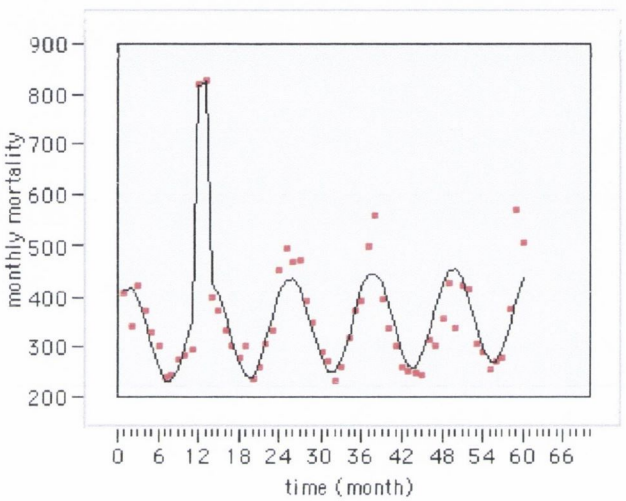


Figure C.7: Actual and predicted monthly all cause mortality occurrence in Ireland 1989-1993 using equation C.6

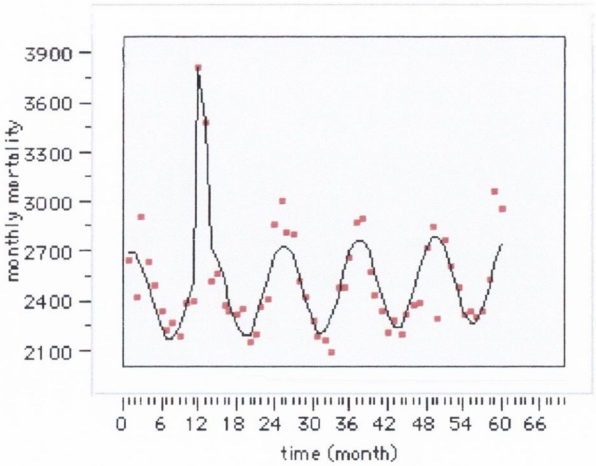


Figure C.8: Actual and predicted monthly respiratory mortality occurrence in Ireland 1989-1993 using equation C.6

| Mortality | % Winter Excess |
|---|---|
| Respiratory Mortality | 73.79 |
| Circulatory Mortality | 29.59 |
| All cause mortality | 28.34 |

Table C.5: Excess winter mortality for Ireland, 1989-1993.

link took the following form:

$$\ln(y_t) = \alpha \cos(\omega t) + \beta \sin(\omega t) \tag{C.7}$$

where $\omega = \frac{2\pi}{52}$, given data are aggregated to a week level.

The excess winter mortality could then be calculated as $\lambda = \sqrt{\alpha^2 + \beta^2}$, the inclusion of the offset term means that $\lambda$ represents the amplitude of the seasonal

curve expressed as a ratio of the mean number of weekly deaths. The amplitude is equal to the height of the peak and the depth of the trough of a wave function, a line can be visualised cutting through the model so that each trough is almost a reflection of the peak, the distance from the line to the very tip of the peak is the amplitude, and in this situation it represents the excess winter mortality.

The above methodology was applied to monthly Irish data; the value of $w$ adjusted accordingly. The model fitted the data reasonably satisfactorily; the graph of the fitted and actual values can be seen in figure C.9. There is still the problem of the peak in the winter of 1989/1990, this was adjusted for using a similar methodology that was applied in the linear regression technique, this model is outlined in Model V. The results of the improved fit are seen in figure C.9. These two graphs show the all cause mortality situation, a similar situation was found with the respiratory and circulatory mortalities.

$$\ln(y_t) = \alpha x_{1t} + \beta x_{2t} + \phi x_{3t} + \gamma x_{4t} \tag{C.8}$$

where:

$$x_{1t} = \begin{cases} \cos(\frac{2\pi}{12}t) & if t < 48 and t > 58 \\ 0 & otherwise \end{cases}$$

$$x_{2t} = \begin{cases} \sin(\frac{2\pi}{12}t) & if t < 48 and t > 58 \\ 0 & otherwise \end{cases}$$

$$x_{3t} = \begin{cases} 2\cos(\frac{2\pi}{12}t) & if 48 \leq t \leq 58 \\ 0 & otherwise \end{cases}$$

$$x_{4t} = \begin{cases} 2\sin(\frac{2\pi}{12}t) & if 48 \leq t \leq 58 \\ 0 & otherwise \end{cases}$$

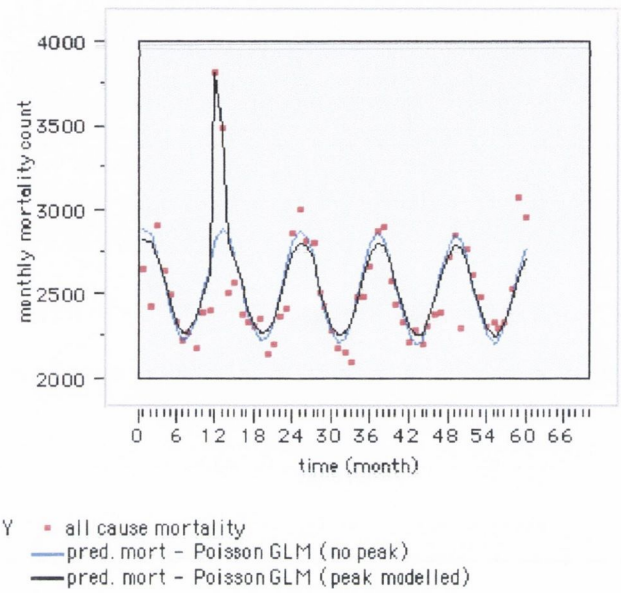


Figure C.9: Actual and predicted monthly all cause mortality rate in Ireland 1989-1993, using equation C.7 and equation C.8

Looking at the graph of equation C.8 the peak only fits two extra points, the rest of the data are not affected by model. As the calculation for excess winter mortality only includes the parameters of the sin and cos. For the non-peak portion of the data there is little difference in using equation C.7 or equation C.8 to calculate the excess. Table C.6 shows the excess winter mortality calculated using equation C.7, the simpler model. The excess winter mortality estimates are lower than previous methods, but the respiratory computation is still over twice as high as the other two excess estimates.

| Mortality | % Winter Excess |
|---|---|
| Respiratory Mortality | 32.99 |
| Circulatory Mortality | 13.44 |
| All cause mortality | 12.94 |

Table C.6: Excess winter mortality for Ireland, 1989-1993. Calculated using equation C.7

If the data are modeled by week there is a lot more variation to account for, hence the fitted model will not be as accurate. Figure C.10 shows the respiratory data by week of year with the predicted values, which were calculated using equation C.7, adjusted for weekly data. For the purposes of this analysis week 1 refer to the first seven days of the year 1989, week 2 refers to the next seven days and so on. From the graph it can be seen that there is a large peak evident, when the previous model for peak was fitted it did not predict the mortality rate in the winter of 1989/1990 very accurately. Table C.7 shows the excess winter mortality calculated using the weekly model. These results are similar to those obtained using the data aggregated by month; no extra information could be gathered by modeling the data by week.

| Mortality | % Winter Excess |
|---|---|
| Respiratory Mortality | 34.41 |
| Circulatory Mortality | 14.64 |
| All cause mortality | 12.94 |

Table C.7: Excess winter mortality for Ireland, 1989-1993. Calculated using equation C.7 on weekly data

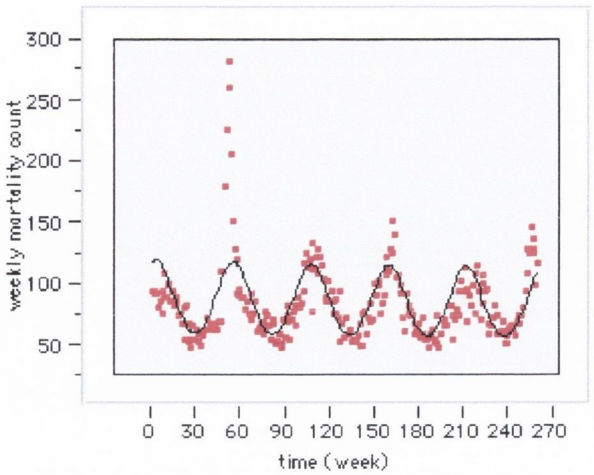


Figure C.10: Actual and predicted weekly all cause mortality rate in Ireland 1989-1993, using equation C.7

## C.3 Discussion and Conclusion

This report has shown a number of different methods that can be used to estimate excess winter mortality. The method used depends very much on the data available and how well it can be modelled. The methods that predefine winter to specific months were a bit too restrictive and were shown to predict the winter months badly. However, in some countries the winter period might occur in set months every year, in such instances it would be appropriate to use a method that predefines winter months.

Modelling the data using a trignometric or a Poisson model seemed to work more successfully. A similar estimate of excess winter mortality was obtained using daily, weekly and monthly data, from this it can be assumed that the aggrega-

tion of data in this case does not affect the result. It should be noted that mortality from respiratory and circulatory disease is common, so the baseline numbers are large. If the event is rare then the aggregation level may affect the final result.

Excess winter mortality is a well known phenomenon, the exact extent of it is questionable. However, using one of the modelling methods that have been discussed ensures a nonbiased estimate, and provides a reliable method by which to compare the excess winter mortality for different areas and different times.

Table C.8 shows the excess winter mortality for each county in Ireland, this was calculated using model C.7. Roscommon has the lowest level of excess winter mortality while Wicklow has the highest level.

| County | % Winter Excess |
|---|---|
| Roscommon | 14.9 |
| Cavan | 22.8 |
| Wexford | 26.6 |
| Galway | 27.2 |
| Longford | 27.8 |
| Sligo | 28.3 |
| Waterford | 28.6 |
| Westmeath | 28.8 |
| Louth | 31.8 |
| Clare | 31.9 |
| Leitrim | 32.6 |
| Kilkenny | 32.8 |
| Kerry | 34.0 |
| Tipperary | 34.1 |
| Carlow | 34.8 |
| Limerick | 34.8 |
| Laois | 35.5 |
| Dublin | 36.9 |
| Mayo | 37.2 |
| Cork | 37.5 |
| Kildare | 37.5 |
| Meath | 38.6 |
| Monaghan | 40.5 |
| Offaly | 43.4 |
| Donegal | 43.6 |
| Wicklow | 46.7 |

Table C.8: Excess winter mortality for each county in Ireland, 1989-1993. Calculated using equation C.7 on weekly data

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