How do we verify a route based forecast?

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ABSTRACT

Route based forecasting services are fast becoming an integral component of many highway authorities winter maintenance strategies, placing an increasing demand on the resources required for the verification of route based forecasts. The current verification technique requires all forecast points along routes to be thermally mapped, an operation that is both time consuming and costly. Whilst this technique is a working solution at present, the increasing number of highway authorities adopting route based forecasts means it is not a long term solution. This paper begins by critically assessing existing verification techniques and explains how existing road outstations and newly developed remote infrared temperature sensors can potentially provide useful data for helping to verify a route based forecast. Thermal mapping however is the only technique that provides information on the spatial variation of road surface temperature around a route, but even this technique is a compromise since the small time window for surveying means it is impossible to survey the full spatial and temporal resolution of the forecast. A new approach to forecast verification is considered which uses hierarchical clustering to group forecast points with similar thermal characteristics into clusters based on a range of geographical and infrastructure parameters. A route based forecast consisting of over 2000 forecast points is potentially reduced over twenty-fold to just 100 points and shown to be verified with a good degree of accuracy, which would represent significant cost and time savings for thermal surveying. The implications of these findings for future research in this area are discussed.

Keywords: route based forecasts, forecast verification, hierarchical clustering

1. INTRODUCTION

Route based forecasting is a service that delivers individual forecasts of Road Surface Temperature (RST) and Road Surface Condition (RSC) for each salting route within a client's road network. Prior to route based forecasts, forecast providers traditionally provided a site specific forecast for a sensor site, with an energy balance model run for these individual sites to provide forecasts of RST and RSC at these locations. These site specific forecasts were based on the foundations of climatic domains and thermal maps, whose inherent limitations are well documented in the literature (Thornes, 1991; Gustavsson, 1999; Chapman & Thornes, 2005). Thermal maps were traditionally used to interpolate from a site specific forecast and assume that every night can be classified into one of a few distinct weather types within which temperature profiles remain consistent. In reality, no two nights are the same, in terms of prevailing weather at a local and micro-climatic level, and particularly in terms of the extent to which conditions such as cloud are present at a given geographic location. It is this limitation that is possibly the greatest strength of route based forecasting. Instead of categorising nights by weather type, route based forecasts take a different approach by modelling the influence of meteorological, geographical and infrastructure parameters on RST and RSC on a night by night basis, thus resolving rather than simplifying a complex reality.

Different forecast providers each have a different approach to generating route based forecasts which results in claims and counter claims as to which approach provides the more accurate results. However, the endorsement of one forecasting product over another is not the aim of this paper. Instead, this paper focuses on a common problem to route based forecasting; *How do we verify a route based forecast?* Whilst this problem may sound simple enough to solve, verification of forecasts needs to be achieved on a scale previously not required. Hence, the development of a robust, reliable, rapid and cost effective verification strategy for route based forecasting will require an entirely new approach to forecast verification. For example, the route based forecasting service provided by WSI uses a spatial modelling approach to forecast RST and RSC every 50 metres along the road network. This equates to 32 forecast points per mile of road, which for a customer with 300 miles of salting routes is nearly 10,000 forecast points to be verified.

Overall, in order for route based forecasts to become an accepted component of a winter forecast service, end users need to have the confidence that the model can accurately predict RST and RSC at *every* point around their road network, not just at sensor sites. The move to route based forecasting requires the accuracy of forecasts around routes and away from sensor sites to be verified. This in turn will increase confidence in the model, which is crucial if the end users are ever to have the conviction to employ selective salting practices such as dynamic routing. Indeed, it is only with increased confidence in models that the end users should be more receptive to the idea of optimising their salting routes (Chapman *et al,* 2006), something which offers the potential for even greater financial savings.

2. EXISTING VERIFICATION TECHNIQUES

2.1 Road Outstations

Since the development of ice prediction strategies in the mid 1980's, road weather outstations (also known as environmental sensor stations) have provided the main source of verification data for site specific forecasts produced by road weather prediction models. However, the accuracy of outstation data is a continual topic of discussion within the road weather community. Thornes (1991) identifies several errors in the measurement of RST using embedded surface sensors. Most of these are systematic errors that can be eliminated or minimised by careful design and installation of the sensor. For example, the albedo, emissivity and thermal properties of the sensor material should all closely match those of the road surface, and the temperature sensor itself should be installed as close to the surface as possible to avoid any lag effects. Even with careful design and installation surface sensors are often prone to error due to poor calibration. Ohio Department of Transport (ODOT) in the USA found this to be the case when performing a bench test of three manufacturers' road sensors to determine their accuracy as part of an RWIS expansion project. The accuracy of several parameters reported by the sensors was tested, including RST, wet/dry surface status, freezing point temperature, chemical percentage and water film depth. None of the sensors performed well under highly controlled experimental conditions, and as a result none were recommended for purchase and deployment by ODOT. All of the sensors had problems with variability of results, and adoption of any by ODOT would have resulted in winter maintenance personnel having to compensate for or disregard entirely some of the measurements (Zwahlen *et al*, 2003).

Even assuming good sensor calibration, embedded road sensors only provide a spot measurement of RST and are therefore unable to provide information on the spatial variation of RST around a road network. This severely limits their use as a verification tool for route based forecasts. This is not to say that spot measurements cannot be useful however. In the United Kingdom, outstations are strategically located to enable climatic variability to be measured, but some countries take a more pessimistic approach and specifically locate outstations at the coldest locations around a road network to give a 'worst case' scenario. Cold spots or thermal singularities such as frost hollows and bridge decks are some of the most difficult locations for road weather prediction models to resolve (Shao, 1998), and outstations located at these problematic sites could provide useful spot measurements for identifying potential weaknesses in a route based forecast model. In countries such as the UK however outstations are rarely located at such problematic sites, and to do so now would require large amounts of investment which highway authorities are unlikely to consider and be able to afford given the continual investments they have made over the past 25 years in their existing ice prediction strategies. A more realistic alternative could involve the use of remote infrared temperature sensors for monitoring RST at sites that are recognised thermal singularities.

2.2 Remote Infrared Temperature Sensors

Recently developed remote road surface temperature sensors from meteorological instrument manufacturers such as Vaisala and Campbell Scientific provide low cost alternatives to traditional outstations and have a number of advantages over traditional outstations that would facilitate their use as a verification tool for problematic forecast sites. Such sensors utilise modern solar power technology and remote GSM/GPRS communications which significantly reduces installation costs as no fixed power and communication lines are required. Whilst many traditional outstations are now equipped with mobile communications, their locations are generally restricted to sites with mains power due to the high power consumption of embedded surface sensors and an increasing demand for outstation cameras capable of live video streaming over IP networks. This gives low power remote infrared sensors a distinct advantage for route based forecast verification since a much greater network coverage is possible, making it feasible to install one or more sensors on every forecast route at a reasonably low cost. These sensors also have the added advantage of measuring RST over a larger surface area compared to the spot measurements of embedded surface sensors, making them less susceptible to erroneous measurements and providing a more realistic indication of the average RST at a particular site. Remote infrared sensors can be susceptible to errors due to traffic however, and whilst sensors such as Cyclo (Vaisala) and IRIS (Campbell Scientific) have traffic filtering algorithms programmed into the systems, the effectiveness of these algorithms under heavy traffic conditions is somewhat unknown and requires further study. Furthermore, these sensors contain algorithms to account for the increased affects of atmospheric radiation on RST under clear sky conditions when other infrared sensors are often inaccurate, but these algorithms contain certain assumptions that can sometimes lead to measurement errors since neither sensor directly measures the actual sky temperature for inclusion into its algorithms.

Despite these potential errors, highway authorities are attracted by the lower costs, easier installation and greater network coverage that remote infrared sensors offer, and an increasing number of highway authorities in the UK and USA are using remote sensors as a low cost alternative to increase coverage of their road network between existing outstation locations. Much like traditional outstations however, remote infrared sensors are unable to provide information for verifying the spatial variation of RST around a road network, certainly not to the same resolution (50m) as the route based forecasting service provided by WSI. To achieve this would require thousands of sensors to be installed around the road network which is wholly impractical. As a verification tool for problematic sites around salting routes however, remote infrared sensors clearly have benefits over traditional outstations, and could potentially be used both for identifying specific weaknesses in forecast models and providing validation data to help to resolve these issues.

2.3 Thermal Mapping

Whilst outstations and remote infrared sensors are unable to verify the spatial variation of RST around a road network, one existing technique does fulfil this requirement. The technique of thermal mapping has been used in applied road climatological studies since the mid 1970’s (Lindqvist, 1976), but it wasn’t until the mid 1980’s that the use of thermal mapping became common practice in winter road maintenance. The technique played a key role in the progression from ice detection to ice prediction, and more than 20 years on the same technique could have an equally important role to play in the progression from climatic domain to route based forecasts. Thermally mapping the road network with a vehicle mounted infrared temperature sensor provides a data set describing the spatial variation of RST around the road network (Shao *et al*, 1997), precisely what is required for verifying a route based forecast. It is well documented that the technique of thermal mapping is subject to a number of random and systematic errors (Thornes, 1991; Gustavsson, 1999; Chapman & Thornes, 2005), but under strict quality control most of these errors can be minimised or eliminated altogether. For example, the recent proliferation of low cost commercial Global Positioning Systems (GPS) has facilitated many improvements in the thermal mapping technique by mitigating several random and systematic errors (Chapman & Thornes, 2005). Most importantly, distance errors due to differences in tyre pressures, cornering at different angles and variations in speedometer accuracy between vehicles have now been eradicated by fixing the exact location of each reading with GPS (Chapman *et al*, 2001a). Other errors such as varying surface emissivity around a route are less easy to resolve, but the potential effects on RST are well documented (Thornes, 1991; Gustavsson, 1999) and are widely accepted as an inherent error of the technique, and perhaps something that can be resolved in forecast models in the future.

The use of thermal mapping as a verification tool for route based forecasts is by no means a new idea. The technique was first used for such purposes by Chapman *et al* (2001a and b) and WSI have successfully been using the technique to verify their route based forecasting service in the UK during the 2006/07 and 2007/08 winter seasons (White, 2007). In its current form however, thermal mapping is a time consuming and costly exercise. The large size of some highway authority road networks means that a single complete survey covering all salting routes can sometimes take days to complete given the time restrictions imposed on surveys by daylight and traffic loads. Research has shown that traffic is a major source of potential error in thermal mapping surveys (Prusa *et al*, 2002; Chapman & Thornes, 2005), with heat fluxes from vehicles having the effect of increasing RST which consequently impacts on the timing of thermal mapping runs. Chapman & Thornes (2005) suggest limiting thermal mapping surveys to the few hours before sunrise on weekends to avoid ‘snapshot’ data collected at any other time which they argue will not be representative of minimum temperatures. Whilst this may be a somewhat histrionic approach, it emphasises the fact that thermal mapping surveys are restricted to a small time window, during which it is impossible to survey the full spatial and temporal resolution of a route based forecast. This somewhat limits the usefulness of thermal mapping as a suitable long term verification technique for route based forecasts. Given the time constraints associated with thermal mapping surveys and the growing demand for verification data as increasing numbers of highway authorities start to adopt route based forecasting services, the time appears to have come for a new verification technique to be developed, one which is robust, reliable, rapid and cost effective. However, unless a new technique allowing verification at the full spatial and temporal resolution can be found, compromises will have to be made. This paper starts to explore new techniques for incorporating this existing verification technology into the new route based forecasting paradigm.

3. A STATISTICAL APPROACH USING HIERARCHICAL CLUSTERING

The spatial modelling approach used in the WSI route based forecasting service takes into account numerous meteorological, geographical and infrastructure parameters, all of which influence RST. With a database of these parameters existing for every 50 metre forecast point along a route, it is possible to group forecast points for a particular route into clusters, the idea being that all points within a single cluster share similar geographical and thermal characteristics. Successful clustering of forecast points provides the potential for much shorter survey routes to be created for verifying route based forecasts, which could represent significant cost and time savings for thermal surveying.

Using a clustering technique known as hierarchical clustering, 2145 forecast points covering a 107 km salting route in Leicestershire, UK (Figure 1) were grouped into clusters based on a number of geographical and infrastructure parameters. The number of clusters was user specified and ranged from a minimum of 10 clusters to a maximum of 100 clusters. Although largely rural, a variety of land uses are encountered along the route ranging from the small urban towns of Coalville and Whitwick in the north to the rural villages of Nailstone, Bagworth and Thornton in the south. A number of different road types are also encountered along the route including motorways, A and B roads and minor unclassified roads, which together cover an altitude range from 80 up to 242m (average 154m).

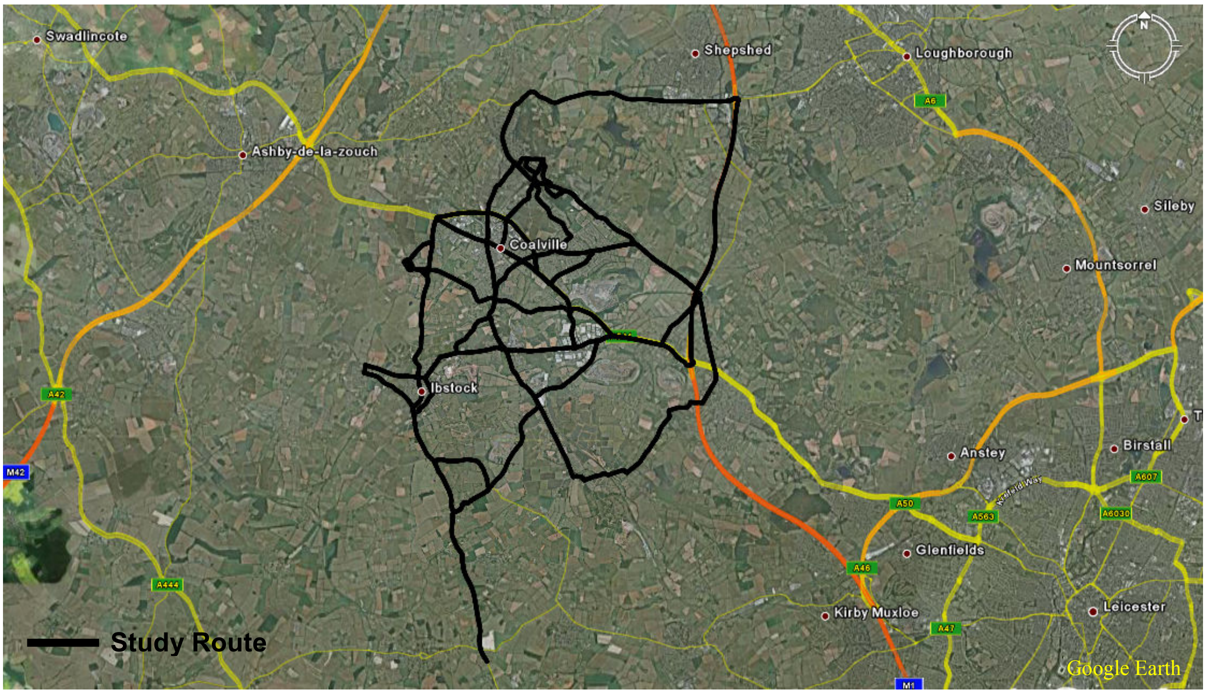

Fig.1. Satellite image overlaid with the 107 km study route in Leicestershire, UK.

Between January and March 2008 the salting route was thermally surveyed using a vehicle mounted infrared temperature sensor (Heitronics CT15) on 20 nights of varying atmospheric stability. Meteorological forecast data for the 20 nights was provided by WSI whose meteorologists carried out daily edits to forecast air temperature, dew point, precipitation, wind speed, cloud cover and cloud height at the forecast site used to drive the RST forecast model. Route based forecasts were then generated for the 107 km study route using WSI's spatial modelling approach. Summary statistics for the 20 nights are shown in Table 1. Forecast and surveyed points were paired together by geo-referencing the points using GIS software, allowing forecast points to be compared with the nearest surveyed value. The average distance between paired forecast and surveyed points over the 20 nights was 5.67 metres. As well as this spatial error, a temporal problem arises since the forecast values are usually output at an hourly resolution, but the surveyed data is recorded continuously during the survey. Geo-referencing the forecast and surveyed points overcomes this issue to some extent since the time each point was surveyed can be used to determine which hourly forecast value to use. To further reduce this error, the model was adjusted to output forecast values at 20 minute resolution, resulting in an average time difference between forecast and surveyed points over the 20 nights of just 5 minutes.

Table 1. Summary statistics showing the accuracy of the route based forecasting service by WSI for the 107 km study route over 20 nights between January and March 2008.

Date	Bias	SD of Bias	RMSE	% residual forecast within ±1°C of residual actual	SD of thermal data (Stability)
21-Jan-08	1.04	0.78	1.30	82.94	0.78 (Intermediate)
24-Jan-08	0.15	0.93	0.94	67.69	1.09 (Extreme)
29-Jan-08	-2.23	0.66	2.33	88.53	0.70 (Intermediate)
31-Jan-08	0.44	0.80	0.91	79.35	0.87 (Intermediate)
03-Feb-08	-2.44	0.62	2.52	90.49	0.37 (Damped)
08-Feb-08	1.05	0.88	1.37	77.81	0.97 (Extreme)
09-Feb-08	0.68	1.18	1.36	63.73	1.19 (Extreme)
10-Feb-08	0.63	1.21	1.36	60.75	1.23 (Extreme)
11-Feb-08	0.16	1.18	1.19	61.07	1.19 (Extreme)
12-Feb-08	0.15	1.38	1.39	52.45	1.42 (Extreme)
14-Feb-08	-4.24	0.55	4.27	93.38	0.47 (Damped)
15-Feb-08	-0.35	0.89	0.96	73.89	0.75 (Intermediate)
16-Feb-08	-2.75	1.19	2.99	61.68	0.95 (Extreme)
17-Feb-08	-1.12	1.20	1.64	61.07	1.14 (Extreme)
20-Feb-08	-1.40	0.59	1.52	91.00	0.73 (Intermediate)
26-Feb-08	0.94	0.72	1.19	85.78	0.86 (Intermediate)
27-Feb-08	-0.56	0.96	1.11	70.26	1.00 (Extreme)
12-Mar-08	1.44	0.69	1.60	87.09	0.73 (Intermediate)
17-Mar-08	-4.25	0.92	4.35	69.70	0.62 (Intermediate)
18-Mar-08	-1.10	0.98	1.47	68.16	1.08 (Extreme)
Mean	**-0.69**	**0.92**	**1.79**	**74.34**	

Of the statistics shown in Table 1, bias, standard deviation of bias and RMSE are common statistics used to assess the accuracy of site specific forecasts (Thornes & Shao, 1991), and such statistics can also be applied to route based forecasts. Averaged bias and RMSE values however may hide significant errors in the model, and further summary statistics are needed to assess the spatial forecasting accuracy of a route based forecast model. The fifth column in Table 1 shows the percentage of residual forecast RST within ±1°C of the residual measured. This statistic is useful for building confidence in a model, since the correct forecasting of RST to within ±1°C for a large percentage of a salting route would indicate that a model has considerable forecasting ability (Chapman & Thornes, 2006).

To assess the usefulness of hierarchical clustering in verifying a route based forecast, forecast and actual RST values for each 50 metre point along the salting route for the night of the 17-Feb-08 were grouped into 10, 20, 30 and 100 clusters. This night was chosen for analysis since the atmospheric conditions during the night were particularly stable, promoting well developed temperature patterns around the route. Hierarchical clustering is a way to investigate grouping within a data set, simultaneously over a variety of scales, by creating a hierarchical cluster tree. The tree is not a single set of clusters, but rather a multilevel hierarchy, where clusters at one level are joined as clusters at the next highest level. The hierarchical clustering algorithm is a bottom-up approach where clustering starts from a single object in the data set (e.g. forecast point) and stops when all the objects are in the same cluster, which is the root of the tree. The process involves firstly analysing the data to find the similarities between every pair of objects in the data set. Using a metric algorithm a distance matrix is created where element *i,j* in the matrix corresponds to the distance between object *i* and object *j* in the original data set. Once the proximity between all objects in the data set has been computed, a clustering algorithm is used to link pairs of objects that are close together into binary clusters (clusters made up of two objects), and to link these newly formed clusters to each other and to other objects to create larger clusters until all the objects in the original data set are linked together in a hierarchical tree (Figure 2).

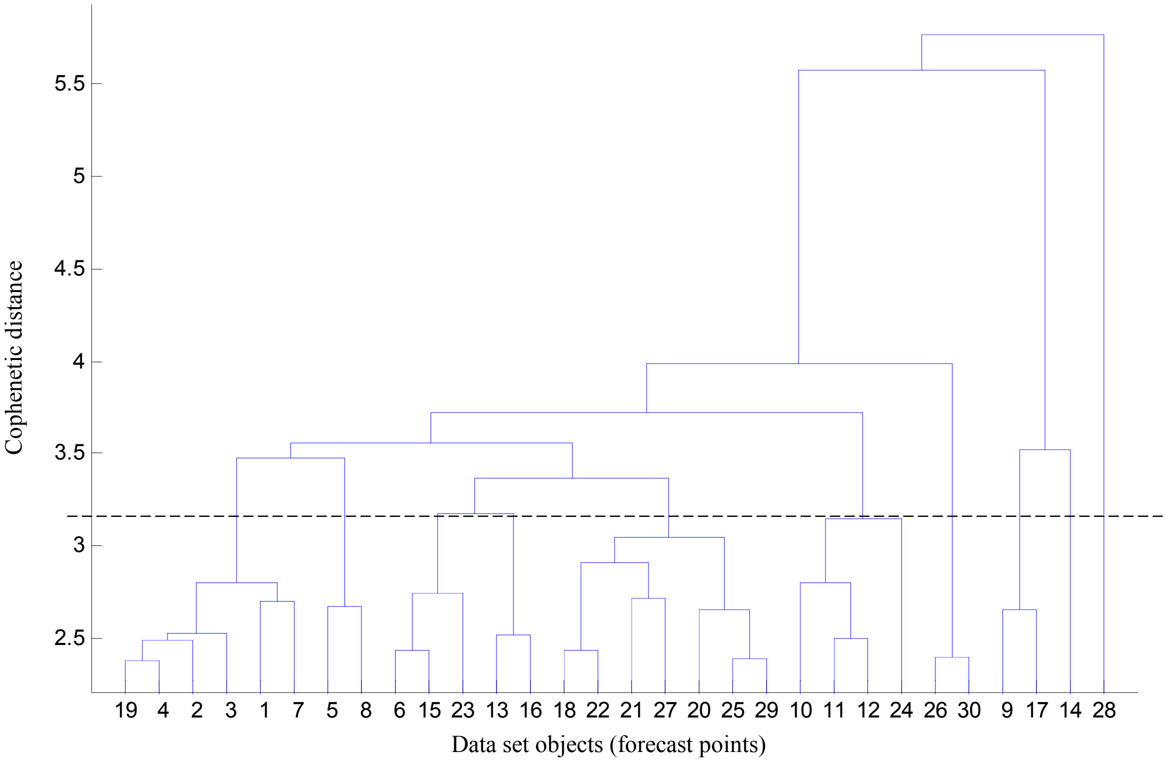

Fig.2. Hierarchical cluster tree for the 2145 forecast points within the 107 km study route, generated using the Euclidean metric and group average clustering algorithms.

Figure 2 shows the top of the hierarchical cluster tree for the 2145 forecast points within the 107 km study route. In a hierarchical cluster tree, any two objects in the original data set are eventually linked together at some level. The height of the link, known as the cophenetic distance, represents the distance between the two clusters that contain those objects. By comparing the cophenetic distances with the original distance matrix, it is possible to calculate the correlation to check the validity of the clustering. The closer the resulting cophenetic correlation coefficient is to 1, the more accurately the clustering solution reflects the original data. Numerous metric and clustering algorithms can be used for hierarchical clustering, and the cophenetic correlation coefficient can be used to compare the results of clustering the same data set using different combinations of these algorithms. The cluster tree shown in Figure 2 was generated using the Euclidean metric algorithm (1) and the group average clustering algorithm (2), giving a cophenetic correlation coefficient of 0.66 indicating a reasonable clustering solution for the data set.

For the Euclidean metric algorithm, given an m-by-n data matrix X, which is treated as m (1-by-n) row vectors $x_1, x_2, \ldots, x_m$, the distance between the vector x_r and x_s is defined as:

$$d_{rs} = \left\{ \sum_{j=1}^{n} \left| x_{rj} - x_{sj} \right|^2 \right\}^{\frac{1}{2}} \tag{1}$$

If n_r is the number of objects in cluster r and n_s is the number of objects in cluster s, and x_{ri} is the ith object in cluster r, the group average clustering algorithm uses the average distance between all pairs of objects in cluster r and cluster s, i.e.

$$d(r,s) = \frac{1}{n_r n_s} \sum_{i=1}^{n_r} \sum_{j=1}^{n_s} dist\left(x_{ri}, x_{sj}\right) \tag{2}$$

The data is grouped into specific numbers of clusters by taking horizontal slices across the hierarchical cluster tree. For example, the horizontal dashed line in Figure 2 intersects 10 links on the cluster tree, and these 10 links partition the objects (i.e. forecast points) in the data set into 10 clusters. Horizontal slicing of the cluster tree was carried out using Matlab functions to group the data set for the night of the 17-Feb-08 into 10, 20, 30 and 100 clusters. For each set of clusters, 20 forecast RST values and the corresponding surveyed values were chosen from each cluster at random, and a further 20 forecast values and the corresponding surveyed values were chosen at random from the entire data set. Statistical analysis of the forecast accuracy was then carried out for the clustered and random values and compared with the statistics for the entire data set for that night to assess the effectiveness of hierarchical clustering as a suitable data reduction technique for the verification of route based forecasts. Since actual rather than retrospective meteorological forecast data was used to generate forecast RST, the percentage of residual forecast RST within ±1°C of the residual measured (actual) provides the best indication of the models spatial forecasting performance, the summary statistics for which are shown in Figure 3.

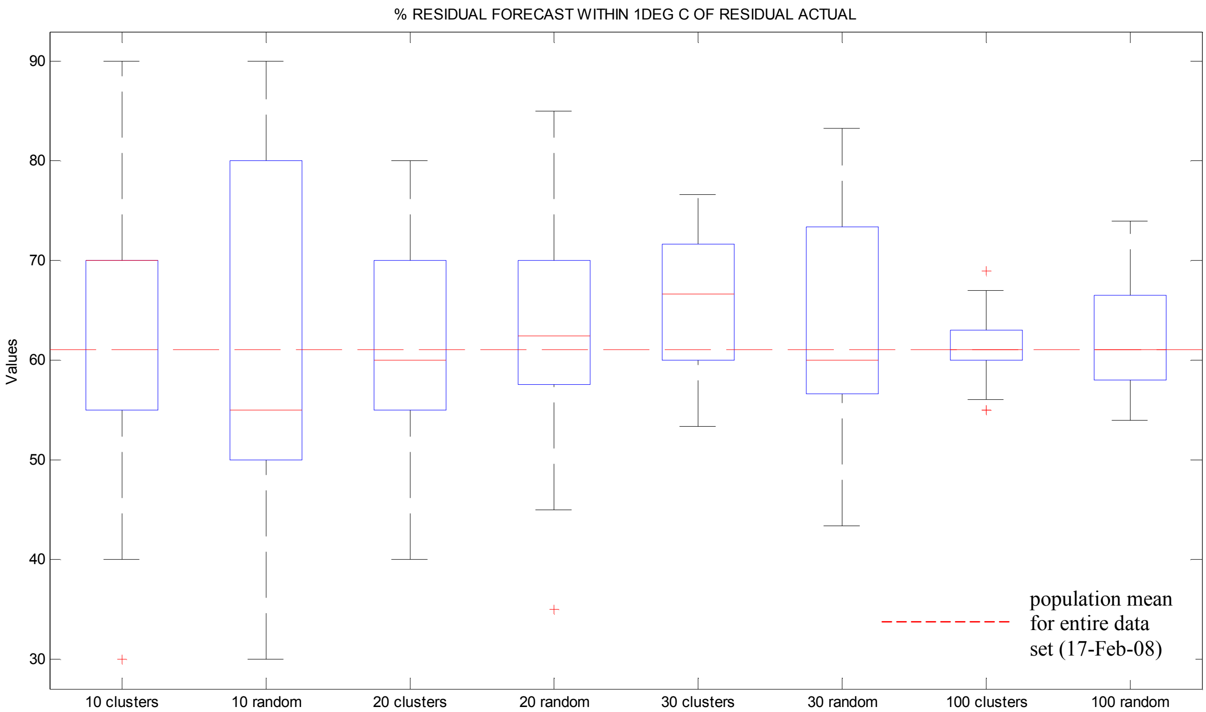

Fig.3. Box plots showing the distribution of values for the percentage of residual forecast RST within ±1°C of the residual measured for 4 sets of clusters (10, 20, 30 and 100). For each set, 20 corresponding forecast and surveyed values were chosen from each cluster at random, and a further 20 corresponding forecast and surveyed values were chosen at random from the entire data set.

4. DISCUSSION & CONCLUSIONS

Figure 3 shows that grouping the data set into clusters and selecting 1 data point from each cluster generally gives less variance in the results than selecting *n* random values from *n* clusters. For a good sample of points to verify a route based forecast, two conditions need to be satisfied:

1. Sample mean is approximately equal to the population mean
2. Small variance around the sample mean

When the data set is reduced to 10 and 20 points a large amount of variance is found in the results, indicating that 20 clusters is currently an insufficient number to assess the accuracy of a route based forecast. When the data set is grouped into 30 clusters less variance is obtained in the results, and finally, with 100 clusters the route based forecast can be verified with a good degree of accuracy. The reduction of 2145 forecast points down to just 100 points is a significant reduction, and would represent significant cost and time savings for thermal surveying. This however would require some form of route optimisation strategy to enable both the time and costs of surveying a shorter 'virtual' salting route to be optimally managed. The use of retrospective meteorological forecast data will improve the accuracy of the statistics regarding actual temperatures and should enable a more thorough analysis of the technique to be undertaken. This, together with the analysis of data covering more nights will be the focus of forthcoming research in order to fully test the robustness of the hierarchical clustering technique.

Hierarchical clustering, or some other clustering technique, may also have potential for being used specifically to identify thermal singularities along salting routes. By grouping forecast points into clusters based on a number of geographical and infrastructure parameters, clusters with few objects are more unique to that road network in the geographical and infrastructure makeup they represent, so forecast points within these clusters can be assessed for thermal singularities. Likewise, clusters containing many objects are common to that road network and could potentially be used for identifying locations for future outstation and/or remote sensor installations. Indeed, if a robust statistical technique can be found to reduce a data set to 10 points per route for example, and these 10 points are able to consistently verify the route based forecast with a good degree of accuracy, this may eliminate the need for thermal surveying to be carried out at all, other than for occasional validation of the statistical technique itself.

This paper has by no means provided the solution to the problem of how to verify a route based forecast, but has merely attempted to highlight ways in which this problem could be approached. Whilst the current technique of thermal mapping is a working solution, the increasing number of highway authorities starting to use route based forecasting services is placing increasing demands on the manpower and resources required to continuously thermally map thousands of miles of road network for the collection of verification data. Existing road outstations and newer remote infrared temperature sensors can provide useful spot measurements for verifying and improving forecast models at sites known to be thermal singularities, but neither possesses the ability to provide information for verifying the spatial variation of RST around a road network which is essential to be able to verify a route based forecast. Statistical techniques represent one avenue of research that is worth investigating, and since the solution appears to require some form of data reduction, dimensionality reduction techniques should probably be the main focus of any statistical research into solving this problem.

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