Passive Thermoelectric Power Monitoring for Material Characterisation

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Abstract

Monitoring deterioration of material properties is important for assessing the structural integrity of engineering components as it may indicate susceptibility to damage. This paper focusses on the example of thermoelectric power (TEP) measurements, which are known to be indicative of thermal and irradiation embrittlement and may therefore act as a proxy metric for material integrity. A passive TEP monitoring technique is proposed which is suitable for permanent installation on engineering components. In passive measurements, the active perturbation (in this case the heating required to create a temperature gradient) is replaced by incidental perturbation from the environment. The reduction in the 'signal' amplitude associated with relying on incidental perturbations may be compensated by increasing the number of individual measurements, facilitated by the greatly reduced power demand of the passive modality. Experimental studies using a stainless steel tube as a test component demonstrate that TEP accuracy of <0.03 μV/°C is achievable with temperature gradients of the order of 2 °C; in many cases of practical importance this is sufficient to track the anticipated changes in TEP associated with thermal degradation.

1. Introduction

The material properties of engineering components may deteriorate over time rendering them susceptible to damage initiation, growth and ultimately failure; this issue is particularly acute in harsh environments that are conducive to degradation processes. It is therefore of interest to monitor material properties as a means of identifying possible damage precursors.

At present, attempts at tracking material properties over time rely on occasional inspections using manually deployable equipment. The fundamental issue with inspections of material degradation is spatial uncertainty. Engineering infrastructure is frequently composed of inhomogeneous materials which may have spatial variation in alloy content, microstructure and prior history. This variability leads to uncertainty between repeat readings as subsequent measurements will be in slightly different locations, so the variability is likely to dominate the subtle temporal evolution associated with material degradation that we wish to measure. Permanently installed sensors offer a means to eliminate the influence of spatial uncertainty; as each measurement will be in exactly the same position and therefore exactly comparable, the sought temporal evolution will be more apparent. Furthermore, manual inspections can only be conducted at convenient opportunities such as outages, whereas permanently installed sensors that are capable of on-load measurements enable frequent measurements that are critical for establishing *trends* in data.

Unfortunately, it is often practically difficult to directly monitor pertinent mechanical properties. As an example, hardness measurements are routinely carried out for the assessment of power station pipework, yet it is not feasible to conduct surface indentation measurements while the component is operational [1]. Fortunately, significant research effort has been invested in investigating a range of alternative metrics that may act as a proxy for the sought property. In particular, electromagnetic properties have been seen as particularly promising due to the high sensitivity to numerous microstructural features and the possibility of simple and robust measurement hardware [2], [3]. Studies into electrical [4]–[6] as well as a range of magnetic and micromagnetic properties [7]–[10] have been conducted. This paper will focus on the Seebeck coefficient, or 'thermoelectric power' (TEP), as an example but many of the issues investigated will be common to a range of other properties. TEP measurements are particularly well suited to monitoring as they are insensitive to changes in geometry which may occur over time and interfere with the measurement [2]. TEP measurements are sensitive to thermal and irradiation embrittlement [3], [11]–[14], hydrogen and nitrogen embrittlement [15]–[17], martensite content [18]–[20], and fatigue damage [21]. In particular sensitivity to the coupled spinodal decomposition of ferrite and sigma phase precipitation in stainless steels [13], [19], [22], [23] makes it a promising technique for use in nuclear power station applications.

Figure 1 shows the results of a previously reported study [2], illustrating the influence of thermal exposure on the TEP of three different ferritic steels (JRQ, A508 and A533). The methodology used to obtain the data was labour intensive; for 76 days the specimens were exposed to elevated temperature for 12 hours per day (equating to 912 hours of total exposure time) then left to cool to room temperature so TEP measurements could be taken. Two consecutive elevated temperatures were used, 410 °C for the first 26 days (312 hours of thermal exposure) followed by 510 °C for the remainder. The decrease in TEP resulting from a thermally activated degradation mechanism is evident at the higher exposure temperature. This labour intensive measurement process, which requires the component to be around room temperature, is not practicable for many engineering applications; the challenge presented in this paper is the development of a TEP measurement methodology that is suitable for continuous monitoring.

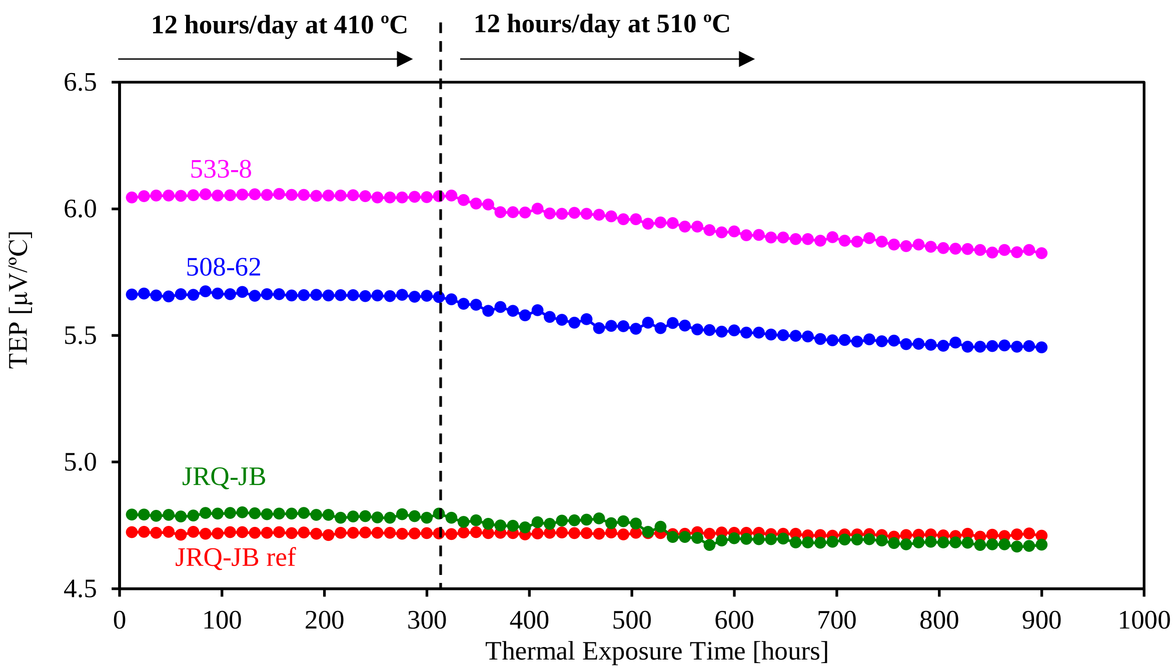
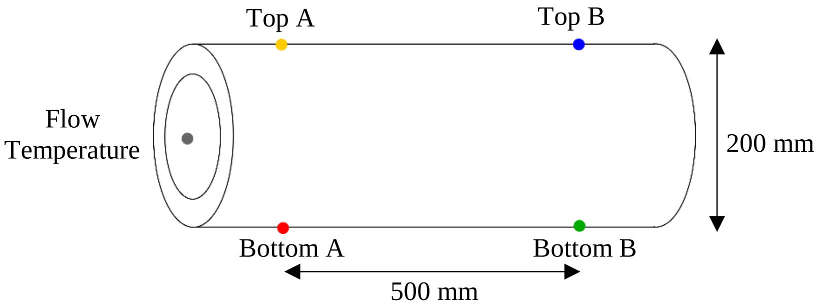


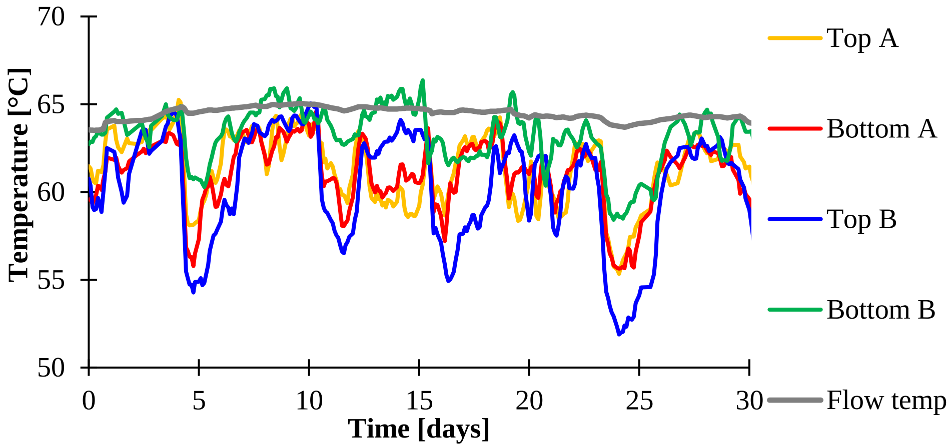
Figure 1: Study demonstrating the influence of thermal exposure on the TEP of three different ferritic steels (JRQ, A508 and A533). A fourth measurement (JRQ-JB ref) was conducted without thermal exposure and is included to verify the repeatability of the measurement process.

Structural Health Monitoring (SHM) systems may be either active or passive [24]. In active monitoring the structure is equipped with actuators that perturb the structure and sensors that monitor the response to the perturbation. In passive measurements the structure is only equipped with sensors, relying on interaction with the environment to provide the perturbation. In active measurement the stimulus may be controlled and therefore 'known' without measuring it, while in passive measurements it is likely to be necessary to measure both the incidental stimulus and the subsequent response.

TEP measurements require a spatial temperature gradient in the component. Conventionally, TEP measurement instruments impose large temperature differentials using active heating elements [25], [26]. The authors recently proposed a four-point TEP measurement technique that may be driven from remote heat sources [27], and it was further suggested that it is possible to adapt this to a passive modality where the heat sources are replaced by small, incidental temperature fluctuations; this concept is explored in the present paper. As an example of the incidental temperature gradients present in engineering components, Figure 2 shows the locations of five temperature sensors installed on a carbon steel pipe together with the corresponding temperatures recorded periodically over 30 days. The pipeline is in an unsheltered location transporting fluid at approximately 64 °C. The data reveals that in this example temperature differences of up to around 5 °C regularly occur between sensor locations, though clearly the nature of the time dependent temperature profile will be highly specific to the application at hand.



(a)



(b)

Figure 2: Temperature data showing the incidental temperature variations that exist in industrial components; data provided by Dr. Audun Oppedal Pedersen of ClampOn AS of Bergen, Norway. a) shows the locations of the five thermocouples. b) shows the data collected over 30 days. Figure originally presented in [27]**.**

The passive modality is attractive as removing the need for actuation (heating) and replacing it with measurement may significantly simplify the hardware, so making it suitable for use in the harsh environments where material degradation is likely. Unfortunately, the incidental perturbations from the environment are likely to be less effective than active perturbations and so the 'signal' will be smaller. However, removing the need to power the actuation reduces the power demand of each measurement and so more frequent or even semi-continuous measurements may be achievable from a finite energy supply; the information can simply be 'harvested' when it is present. In this study, it is proposed that equivalent confidence in estimators may be obtained from combining numerous high uncertainty measurements as from a small number of low uncertainty measurements. The feasibility of the passive TEP monitoring technique is investigated.

This paper will be structured as follows. A background to TEP measurements will be given for context, followed by a statistical analysis on the gradient estimates TEP estimates rely on. Experiments will be used throughout to illustrate the different concepts, including an illustration of the passive TEP measurement concept on a stainless steel tube. Finally, discussion will be devoted to further considerations required to transfer the methodology to an industrial context, together with reflection on the broader applicability of passive measurements.

2. Background to Thermoelectric Power Measurements

A brief introduction to contact thermoelectric power measurements will be given in this section to provide background for the remainder of the study. This introduction is an abbreviated and simplified version of that given in (10). An example experiment will be used in this section to demonstrate the measurement process, introduce the experimental arrangements and generate an example data set; TEP measurements of a 99.5% purity nickel sample are used due to the availability of reference values available in the literature for validation.

Contact TEP measurements simply require two thermocouple 'electrodes' galvanically joined to the surface of the monitored component, as illustrated in Figure 3. A spatial temperature differential must exist in a component to 'drive' the measurement; in existing inspection equipment the temperature gradient is introduced by an active heating element integrated into one of the electrodes, but it is proposed in this paper that incidental heating or cooling will produce thermal gradients that may be exploited for the measurement.

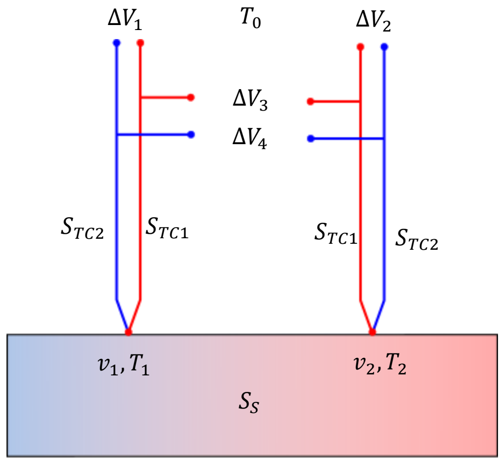


Figure 3: Schematic illustration of the passive TEP measurement arrangement. Two thermocouples are joined to a component where a temperature gradient is present. Four voltages are monitored: two thermocouple measurements from which the temperature difference is inferred, and two from each similar thermoelement pair from which the thermoelectric potential in the component is inferred.

The temperature differential, $T_1 - T_2$, produces a thermoelectric potential difference, $v_1 - v_2$, dependent on the sought Seebeck coefficient of the material, S_S, by definition,

$$v_2 - v_1 = \int_{T_1}^{T_2} S_S dT \approx \bar{S}_S(T_2 - T_1) \tag{1}$$

We eliminate the need for integration by assuming that the thermoelectric power is linearly temperature dependant between T_1 and T_2; the Seebeck coefficient at the reference temperature $(T_1 + T_2)/2$ is denoted throughout by the overbar. To calculate, $\bar{S}_S$, the four potential differences labelled ΔV_1-ΔV_4 in Figure 3 are measured. The temperatures T_1 and T_2 are inferred from ΔV_1 and ΔV_2 using the standard thermocouple method. The potential difference $v_2 - v_1$ may be inferred from either ΔV_3 or ΔV_4. The potential differences, ΔV_3 and ΔV_4, are composed of the thermoelectric potential from the Seebeck coefficient and temperature difference of the component, $T_2 - T_1$, and additionally the thermoelectric potential from the Seebeck coefficient and temperature difference of each of the thermoelements, $T_1 - T_0$ and $T_2 - T_0$, where T_0 is the cold junction temperature,

$$\Delta V_3 = \bar{S}_S(T_2 - T_1) + \bar{S}_{TC1}(T_1 - T_0) + \bar{S}_{TC1}(T_0 - T_2) \tag{2}$$

$$\Delta V_4 = \bar{S}_S(T_2 - T_1) + \bar{S}_{TC2}(T_1 - T_0) + \bar{S}_{TC2}(T_0 - T_2) \tag{3}$$

so,

$$\Delta V_3 = (\bar{S}_s - \bar{S}_{TC1})(T_2 - T_1) \tag{4}$$

$$\Delta V_4 = (\bar{S}_s - \bar{S}_{TC2})(T_2 - T_1) \tag{5}$$

The 'slope method' [28]–[31] may be used to estimate $\bar{S}_s$ by plotting ΔV_3 or ΔV_4 against $T_2 - T_1$, as illustrated in Figure 4; the slope is the central term of Equation (4) or (5) and S_{TC1} and S_{TC2}, are well documented for common thermoelements [32].

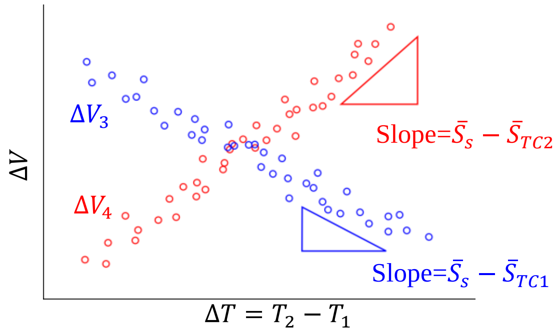


Figure 4: Illustration of the 'slope method'.

This measurement process is demonstrated using a 99.5% nickel sample of dimensions 5 x 52 x 52 mm, using the experimental arrangement illustrated in Figure 5. We seek to investigate the influence of the available temperature gradients on the accuracy of the measurement; although the ultimate aim is to utilise ambient heating and cooling, for the purpose of investigating the influence of different measurement parameters, two power resistors are used as heating elements. Additionally, the whole assembly is placed in an environmental chamber to control the mean temperature.

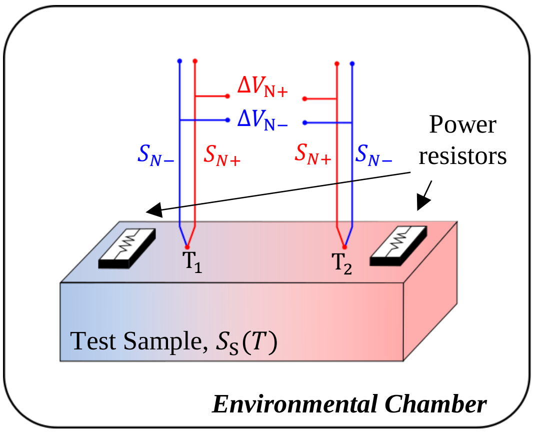


Figure 5: Illustration of the experimental arrangement used to measure the TEP of the 99.5% pure nickel sample, two power resistors are used to control the temperature difference and the whole assembly is placed in an environmental chamber to control the mean temperature. N-type thermocouples are used with thermoelements denoted as 'N+' and 'N-'.

Throughout this paper, N-type thermocouples are used with thermoelements denoted throughout as 'N+' and 'N-'. For clarity of presentation the potential differences ΔV_3 and ΔV_4 will be referred to as $\Delta V_{\mathrm{N+}}$ and $\Delta V_{\mathrm{N-}}$ respectively, corresponding to the two different thermoelements.

The temperature of the opposite ends of the component are alternately gradually raised and lowered by controlling the current through the power resistors, the result being shown in Figure 6 a). It should be noted that the relatively modest temperatures used in this experiment are in contrast to those used in commercial engineering instruments which typically use 'hot-tip' electrodes heated to around 100 °C [25]; this experiment is a step towards using incidental environmental heating. The slope method for this case is illustrated in Figure 6 b), subsequently $\bar{S}_s$ may be found using literature values of $\bar{S}_{N+}$ and $\bar{S}_{N-}$ for the relevant temperature.

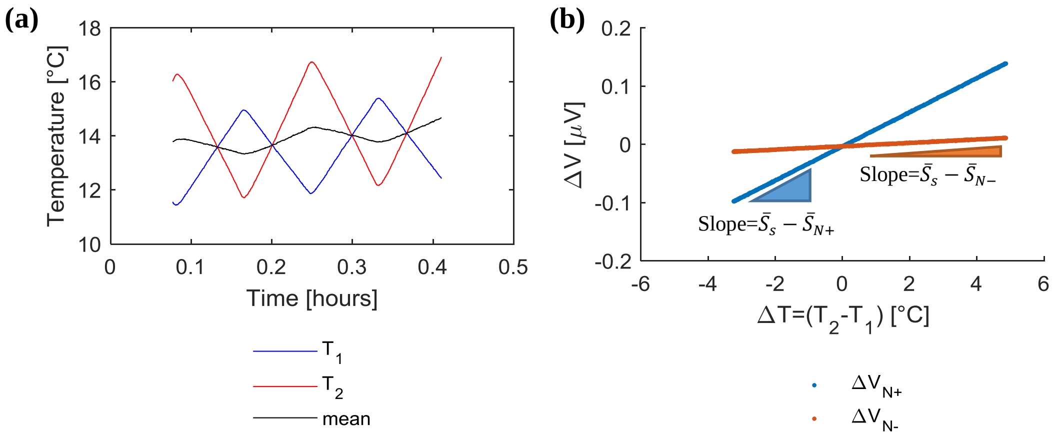


Figure 6: Illustration of the TEP measurement processing. a) the temperature at two locations is measured using thermocouples in order to establish the temperature differential and mean temperature. b) the thermoelectric potential is plotted against temperature difference, from the slope estimate the TEP is calculated using Equation (4) and (5).

The Seebeck coefficient is strongly dependent on temperature, and therefore it is necessary to attribute the calculated value to a mean temperature; fortunately, the mean temperature is obtained as a by-product of the TEP measurement. To illustrate this, the mean temperature of the experiment assembly was gradually raised so that the TEP could be evaluated at a range of temperatures, as illustrated in Figure 7 a). This allows comparison with literature values, confirming that the experimental procedure is sound, as illustrated in Figure 7 b). The temperature dependency is an important consideration for TEP measurements; it is necessary to monitor the TEP as a function of temperature, introducing an additional dimension to the measurement.

The central concept in this study is that the range of temperature differentials may be reduced from the ~8°C shown in Figure 6, so that it may even be driven from incidental gradients, as the remainder of this paper investigates.

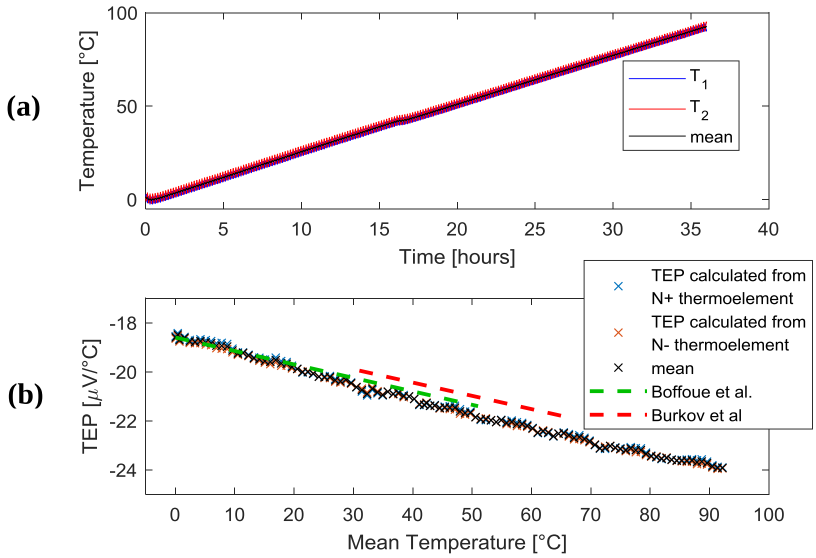
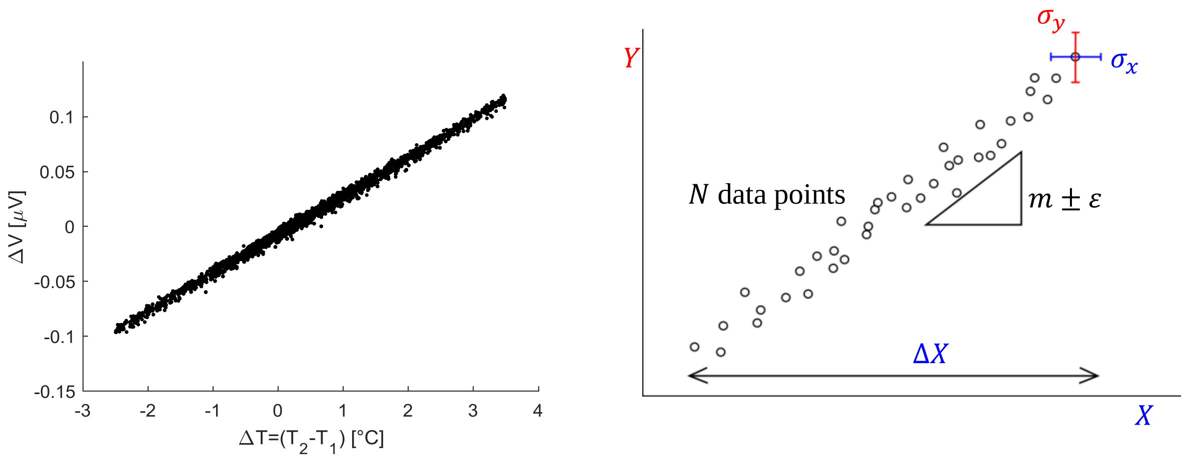


Figure 7: a) Data showing the change in mean temperature and temperature differential of the sample. For a detailed view over a small temperature range, see Figure 6. b) TEP calculated from the data in a) and Equation (4) and (5). Also included is reference data from [28], [33]**.**

3. Uncertainty in estimates of linear regression

TEP measurements are dependent on the accuracy of estimates of $\Delta V/\Delta T$ derivative, such as that shown previously in Figure 6 b). Adopting a passive modality that relies on incidental heating will reduce the range of temperature differentials available for correlation. Intuitively, reducing the range of data will have a detrimental effect on the confidence in derivative estimates, but increasing the number of data points will improve confidence; this hypothesis will be explored in this section.

The analysis in this section will be applicable to measurements of other material properties where a stimulus and reaction are to be correlated. Figure 8 a) presents a portion of data from the nickel experiment introduced in Section 2 while Figure 8 b) shows a general schematic, where the independent variable ΔT is referred to as X and the dependent variable ΔV is referred to as Y; the parameters which determine the confidence in gradient estimates are also labelled. Each of the N measurement pairs, x_i and y_i, have standard deviations of σ_x and σ_y respectively. The measurement pairs are correlated to find the sought gradient m which has an uncertainty, ε.



(a) **(b)**

Figure 8: a) Thermoelectric potential against temperature difference scatter plot for a portion of the 99.5% nickel experiment presented in Figure 7 (mean temperature of 57 – 63 °C). b) Illustration of a generic scatter plot with parameters that determine the confidence of a derivative estimate labelled.

As there is measurement uncertainty associated with both the x and y measurements the derivative should not be found using a linear least-squares regression but rather a 'Deming' regression [34], [35], calculated as,

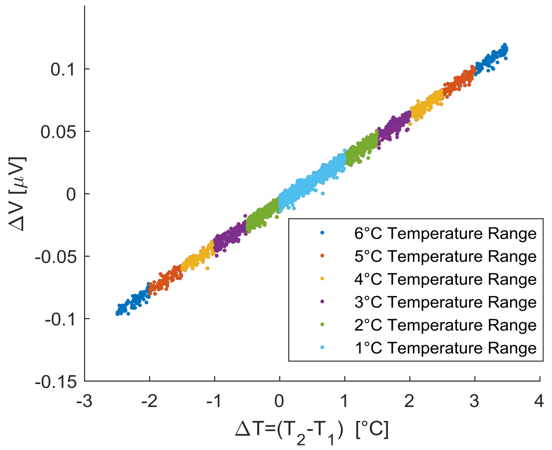
$$m = \frac{S_{yy} - \lambda S_{xx} + \sqrt{\left(S_{yy} - \lambda S_{xx}\right)^2 + 4\lambda S_{xy}^2}}{2S_{xy}} \tag{6}$$

where S_{xx} is the variance of x, S_{xx} is the variance of y, S_{xy} is the covariance of x and y and λ is the ratio of the standard deviations of individual measurements σ_x / σ_y. In the present example both variables (the temperature difference and the thermoelectric potential respectively) are quantified using the same equipment in a similar fashion and so we will assume $\lambda = 1$, but this may not be the case in other applications. The uncertainty in derivitive is not easily derived analytically but may be calculated numerically using a 'jackknife' method [34], [35]. The jackknife method is a resampling technique for estimating a statistical parameter by systematically omitting each data point in turn, estimating the parameter and finding the mean [36]. By creating artificial datasets of correlated variables and using the jackknife method reveals that the standard deviation of a derivative estimate is,

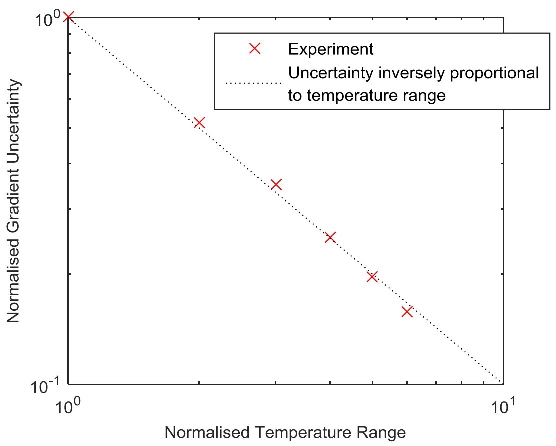
- $\sigma_m \propto 1/\sqrt{N}$ (number of observations)
- $\sigma_m \propto 1/\Delta X$ (range of independent variable)
- $\sigma_m \propto \sigma_x$ (individual uncertainty)

This shows that the relative variance (the individual measurement variance divided by the range of the independent variable) together with the number of measurements, governs the confidence in estimates.

These findings are directly applicable to TEP measurements, and may be used to investigate the feasibility of a passive modality. The data from the nickel sample experiment, shown previously in Figure 8 a), may be used as a demonstration. The data was segmented into increasing temperature differential windows, each increasing by 1°C and with the same mean, as shown in Figure 9. 1000 data points were taken from each window and the uncertainty associated with each Deming regression was calculated using the jackknife method. As anticipated, there is inverse proportionality between derivative uncertainty and the temperature range, as shown in Figure 9 b). While the temperature was cycled in a regular way (as shown in Figure 6 a), taking data randomly begins to resemble potentially available data in in applications such as that shown in Figure 2.



(a)



(b)

Figure 9: Demonstration of the influence of range of data on the uncertainty in derivative estimates using the 99.5% Nickel sample shown previously in Figure 8 a). a) Thermoelectric potential against temperature difference. An increasing range of temperature difference data is used to estimate the derivative. b) The relative uncertainty in derivative uncertainty as a function of normalised temperature range.

Similarly, the influence of the number of data points contributing to each derivative estimate may be demonstrated. Increasing numbers of data points were randomly selected from the data set shown in Figure 8 a); the number of data points included in each estimate was increased from 300 to 2400 in steps of 300. Again, the uncertainty associated with each derivative estimate was calculated using the jackknife method. There is an inverse relationship between the derivative uncertainty and the square root of the number of measurements, as shown in Figure 10.

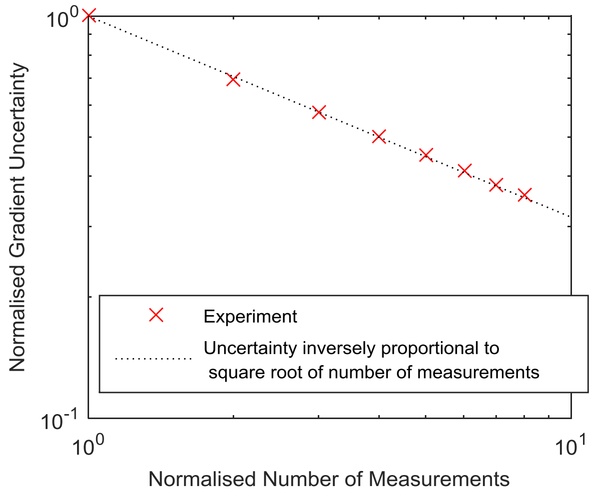


Figure 10: Demonstration of the influence of number of data points on the uncertainty in derivative estimates. Increasing number of data points are used to estimate the derivative of the data shown in Figure 9.

This study shows that the random uncertainty associated with a derivative estimate may be improved by either increasing the range of the independent variable or increasing the number of measurements. Equally, it indicates that the reduction in certainty from reducing the measurement range may be compensated by increasing the number of measurements. Unfortunately, the discrepancy between the $1/\Delta X$ and $1/\sqrt{N}$ does not favour passive monitoring; a decrease in measurement range will require the number of measurements to increase by the proportional decrease in range squared.

Compensating measurement range with number of measurements may be taken to an extreme when moving to an ‘information harvesting’ approach: the parameter range may reduce significantly when relying on incidental changes, but equally, as the measurement becomes ‘passive’ then the number of readings may also increase by orders of magnitude. Equivalent confidence may be achieved with a 10-fold reduction in the temperature differential range (from 10°C to 1°C) and a 100 fold increase in measurement frequency (say one measurements every four days as opposed to 1 per year). This increase in measurement frequency is entirely feasible and additionally the continuous, *in situ* measurements, provides improved integrity awareness.

It is important to emphasise that the key parameter is temperature differential *range*. In order to ensure a wide range of temperature differentials the sampling method and time scales involved in the temperature fluctuations are of great importance. There is little benefit in collecting a large number of near-instantaneous samples at a single thermal state; instead it is preferable to capture data over the fullest range of temperature differentials available, populating the ΔV-ΔT scatter plot, as indicated in Figure 11. In industrial applications this will need to be considered and is likely to result in the need for non-constant sampling rates, instead preferentially harvesting diverse data. Further, this analysis assumes that we are measuring TEP at a single mean temperature. As TEP is temperature sensitive, and we expect changes in mean temperature, this must also be taken into account as addressed in the following section.

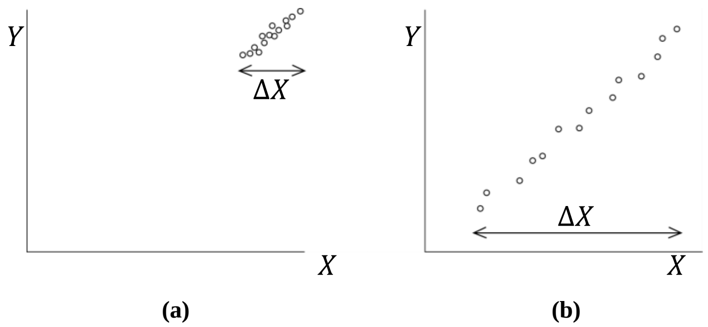


Figure 11: Illustration highlighting the importance of sampling. a) poor sampling: despite the presence of a large temperature differential, the samples are taken over a limited range which would lead to poor confidence in the derivative estimate, b) better sampling: the same number of data points are taken over a larger range of temperature differentials, leading to greater confidence in the derivative estimate.

4. TEP Monitoring of a Component in Simulated Environmental Conditions

An experiment was conducted in order to investigate the use of the passive TEP monitoring technique by simulating conditions that may be expected in real engineering components. Results will be evaluated in the context of Figure 1; in order to monitor the changes in TEP that are of the order of 0.2 μV/°C, an approximate target accuracy of 0.02 μV/°C is required to accurately discern the trends in TEP attributed to thermal degradation. This accuracy should be achievable from a temperature differential range of the order of 5 °C, a value derived from Figure 2.

A stainless steel tube (ASTM A213, one inch diameter, 0.12 inch wall thickness, seamless, 304 stainless steel) was used as an example. Two N-type thermocouples were spot welded to the tube separated axially by 206 mm. Two power resistors were then clamped with a 464 mm axial separation, allowing controlled 'differential' heating (where the power through the two resistors is different in order to create a temperature differential) and 'common-mode' heating (where the slowly changing average power through both resistors is the same). Controlled heating enables simulation of conditions that might be found in a real component exposed to a combination of operational and ambient conditions.

Four periods of test conditions were imposed, as summarised in Table 1. Throughout the whole experiment, differential heating was applied sinusoidally to create the range of temperature differentials that the measurement relies on. Between Periods 1-3 the differential heating range was approximately halved each time, simulating cases where incidental differential heating is increasingly weak. Changes in the mean temperature of the component reflect changes of the ambient temperature, but the mean temperature of the component is systematically higher than that of the ambient temperature by an offset temperature that depends on the constant average power dissipation of the two heating resistors. Period

4 has the same differential heating as Period 2, but a much slower sinusoidal common-mode heating is now added, creating a periodic drift in mean temperature. The heating imposed in each of the successive periods creates increasingly challenging conditions from which to 'harvest' TEP measurements.

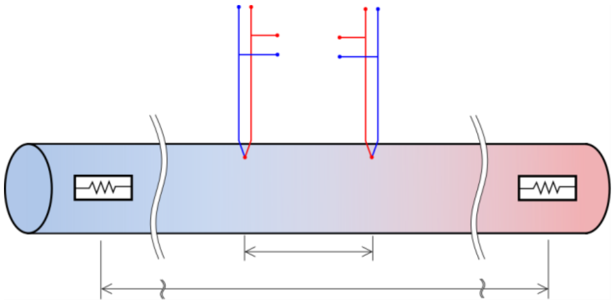


Figure 12: Illustration of the 304 stainless steel tube experiment. Two N-type thermocouples are welded to the surface of the component and two power resistors are adhered to the tube in order to introduce controlled changes in mean temperature and temperature differential.

Table 1: Summary of the test conditions imposed on the stainless steel tube, together with the standard deviation of the TEP and temperature compensated TEP, plus the 95% confidence interval of temperature compensated TEP estimate assuming 96 independent readings.

Period	Temperature Differential Range from Differential Heating [°C]	Nominal Mean Temperature Range from 'Common-mode' heating [°C]	TEP Standard Deviation [µV/°C]	TEP Standard Deviation with Temperature Compensation [µV/°C]	95% confidence interval of temperature compensated TEP estimate [µV/°C]
1	6.58	1 (ambient – temperature controlled lab)	0.0339	0.0338	0.0068
2	3.37	1 (ambient – temperature controlled lab)	0.0636	0.0639	0.0128
3	1.81	1 (ambient – temperature controlled lab)	0.1292	0.1263	0.0253
4	3.20	10 (forced)	0.0759	0.0608	0.0122

The results of the experiment are presented in Figure 13 and standard deviations are shown in Table 1. Between Period 1 and 2 the temperature differential was approximately halved (factor of 1.95); as anticipated this caused the TEP standard deviation to approximately double (88% increase). An equivalent relationship occurs when the temperature differential is halved again between Period 2 and 3. In order to compensate for the two-fold decrease in temperature differential range the number of measurements would have to increase by a factor of four to maintain the same confidence in TEP estimates. As the error between successive estimates is dominated by random uncertainty, additional confidence in the TEP estimate may be obtained by combining a number of estimates. As an example, in Period 1 there are 96 independent TEP estimates (where the data from each hour forms an independent estimate); combining this with the standard deviation shown in Table 1 gives a 95% confidence interval of 0.0068 μV/°C. This accuracy is clearly sufficient to discern the trends in TEP resulting from thermal degradation indicated in Figure 1. The TEP uncertainty obtained during Period 3 of ±0.0258 μV/°C is around the borderline of the accuracy required to monitor the trends illustrated in Figure 1; increased confidence may be obtained by increasing the number of measurements contributing to the average, either by increasing the sample rate or by averaging time.

In Period 4 a mean temperature change is imposed. Due to the temperature dependence of TEP, the mean temperature variation causes a drift in TEP and subsequently an increase in the standard deviation. As this is not a random error it cannot be simply overcome by increasing the number of measurements; we must introduce a mean temperature 'axis' to the monitoring.

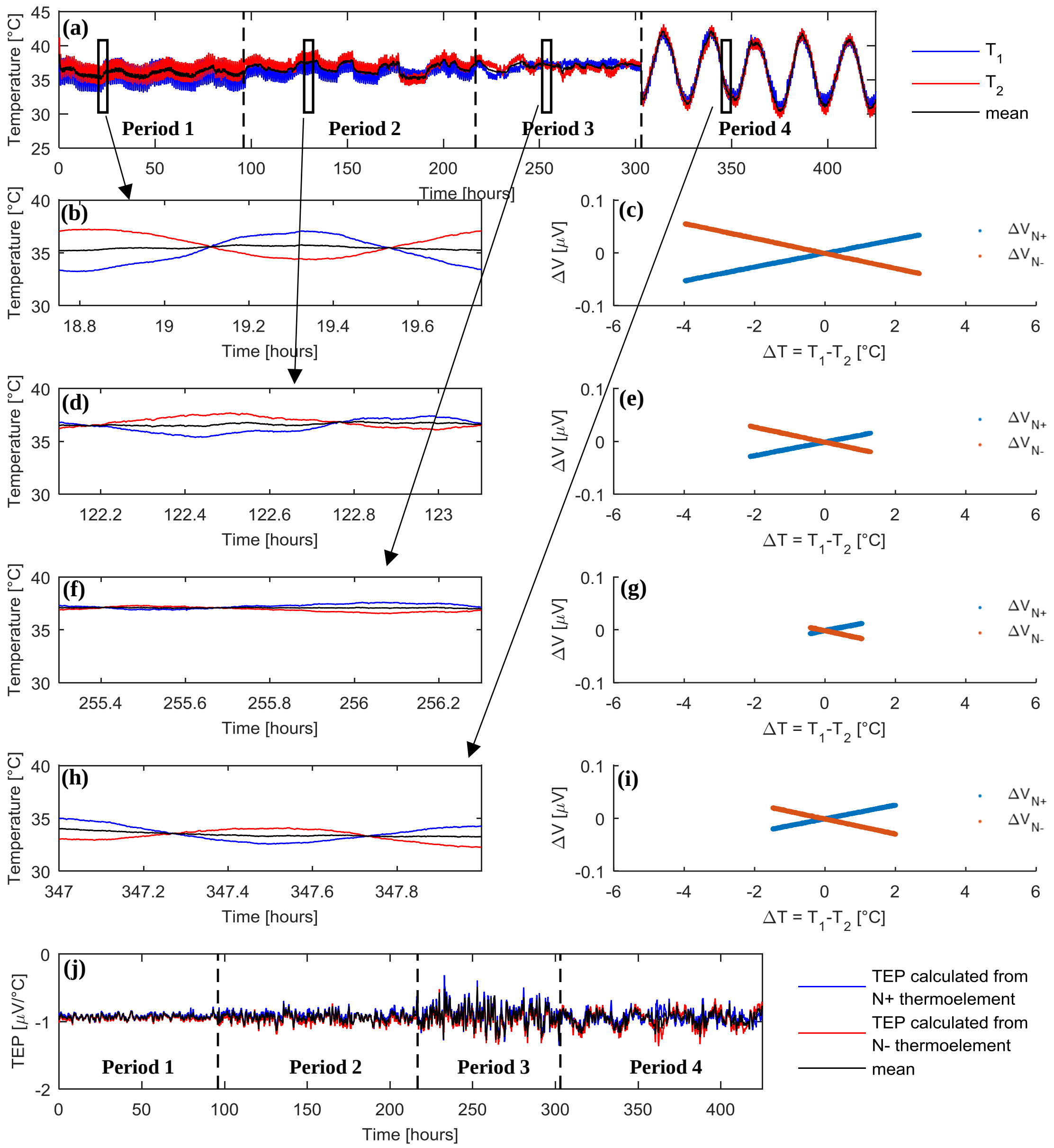


Figure 13: Results from stainless steel tube experiment. a) the two thermocouple measurements and the mean measurement over the four testing regimes.
b)-c) Shows an example data set from Period 1, d)-e) shows Period 2, f)-g) shows Period 3, h)-i) shows Period 4. The left figures show an example period of temperature against time, the right figures show the same set of data as thermoelectric voltage against temperature differential.
j) Shows the subsequently calculated TEP over time.

Figure 14 a) shows a reference measurement for a sample of 304 material taken using the same process as for high purity nickel (Figure 7) to establish the expected temperature dependence, while Figure 14 b) shows the temperature dependence evaluated from the data gathered during Period 4. It shows that if the mean temperature were to change from 0°C to 80°C we would expect a change of 0.85 μV/°C, which would of course dominate any random uncertainty. It is not surprising that there is an offset between the reference sample and tube measurement sets as though they are both nominally 316 stainless steel they are entirely distinct samples (different supplier, form, prior history etc.); it is this kind of subtle change in TEP that we seek to measure. Temperature compensation can be easily applied using linear regression. Figure 14 c) shows the result of temperature compensation for Period 4. The standard deviation of the temperature compensated TEP data is summarised in Table 1, but of course the improvement is only significant in Period 4. Temperature compensation is shown to reduce the standard deviation down to the level of Period 2, which has equivalent differential heating but no ‘forced’ change in mean temperature, showing the influence of mean temperature change is effectively suppressed.

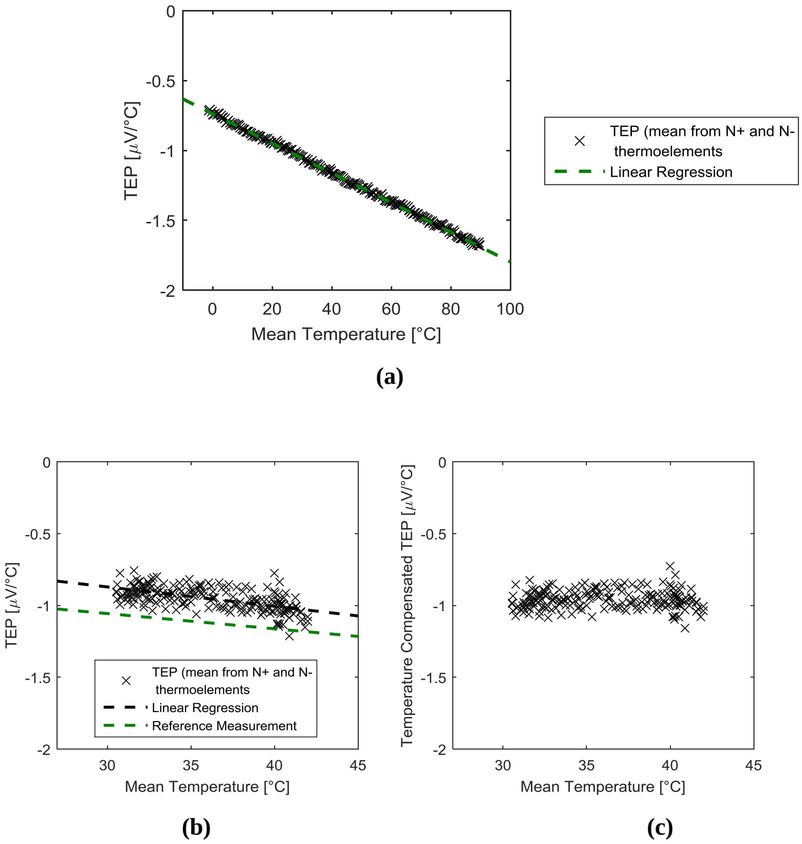


Figure 14: a) Reference TEP measurement, carried out over a range of temperatures using a 316 bar specimen in an environmental chamber. b) The TEP data from Figure 7 plotted against mean temperature, the reference measurement is from b). c) The same TEP data following temperature compensation.

5. Discussion

The experiments in this study demonstrate the feasibility of passive monitoring of TEP in engineering components. The application of this technique to an industrial setting requires a number of further, application specific, considerations.

While a passive measurement does not have to power an actuator to drive the measurement, there is nonetheless an energy expense per measurement. Any analogue circuitry required in the receiver chain and the ADC require energy investment, plus any local computation and wireless communication if required. This cost must then be considered in the context of the available power supply; if there is an effectively unlimited mains supply then measurements may be taken more or less continuously, if however the supply it is limited, either with a finite battery or limited by what is available from energy harvesting [37] then the number of measurements may also be limited. For the purpose of this discussion, we will assume the power supply is limited.

The nature of the temperature fluctuations needs to be taken into consideration. Clearly, changes in sources of differential heating are beneficial, providing a range of temperature gradients, while changes in 'common-mode' heating are unhelpful. In many situations the two are coupled, for example large spatial temperature gradients may exist during transients. In other situations, the mean temperature may be effectively anchored to a nominal temperature by an industrial process while a temperature differential may be driven by environmental conditions or minor perturbations. The latter represents a much more desirable situation for TEP monitoring.

The time scales involved in the data collection and both temperature differential and mean temperature changes are important to consider. There is little additional benefit in collecting a large number of measurements at one temperature differential; instead, it is necessary to populate the ΔV-ΔT scatter plot with as wide a range of data as possible. Additionally, if there are significant changes in mean temperature that need to be considered, it is also important to populate the TEP-temperature space. Clearly, not all data points provide equal statistical value. With this in mind it is possible that a system may be developed that preferentially invests its limited energy supply in harvesting data that is of most value.

The analysis in this study focusses on the statistical uncertainty associated with a derivative. This is pertinent beyond the example of TEP measurements and provides insight into the possibility of passive monitoring of other properties. When taking a measurement we are interested in quantifying the response to a stimulus, in this case the thermoelectric potential from a temperature gradient; we must be able to quantify both the thermoelectric potential and the temperature with the derivative of the two providing the sought information. If we were to try to monitor electrical resistivity we would seek to measure the potential difference and the current flux between two points and quantify the derivative between the two quantities in an equivalent process. Unfortunately, while the potential difference may be feasibly measured, the current is not trivial to measure accurately and so a passive monitoring modality is not practicable; we must be able to measure both the incidental stimulus and response to enable passive monitoring.

Another major benefit of moving to a passive modality is the potential for simplifying sensor hardware by removing the need for actuation. In the case of the TEP example, an active sensor would need to incorporate a heating or cooling element to drive the temperature differential in addition to the two thermocouples; this represents an addition that would preclude use in many industrial environments. Removing the need for actuation may therefore present new opportunities in monitoring, even if the energy proposition is not beneficial.

6. Conclusions

A passive TEP monitoring technique has been proposed that avoids the need for active heating by relying on incidental temperature gradients. Accurate measurements are achieved despite the modest temperature gradients by combining large numbers of measurements; an increased measurement rate is facilitated by the low power 'passive' operation. TEP measurements which are accurate to <0.03 μV/°C have been demonstrated with a temperature gradient range of <2 °C. The systematic influence of changes in mean temperature may be addressed by simple temperature compensation techniques.

In order to transfer the TEP monitoring technique to an industrial setting, application specific factors will need to be considered. The anticipated performance of the measurement technique will depend on the nature of the changes in temperature that might be expected. Large spatial temperature gradients are beneficial yet large changes in mean temperature are problematic. If the energy available for measurements is limited then it may be worth developing a 'smart' system that preferentially harvests data of highest statistical value.

The passive concept presented in this study may be applicable to monitoring other properties. Many properties require correlation between a stimulus and response. The passive modality is viable in situations where controlled purposeful stimulus may be replaced by measurement of the incidental stimulus. The shift from active actuation to measurement may result in simpler and more robust sensors, providing new opportunities for permanently installed sensors, particularly in harsh environments.

The passive TEP monitoring system is suitable for installation in challenging industrial situations. Of particular interest is the monitoring of infrastructure for nuclear power generation, which may be subject to thermal and irradiation embrittlement. Monitoring the degradation of material properties will provide a real time indication of the integrity of the components, allowing for improved infrastructure management.

Acknowledgments

The data of Figure 2 was provided by Dr. Audun Oppedal Pedersen of ClampOn AS of Bergen, Norway.

This work was supported by the UK Engineering and Physical Sciences Research Council via the UK Research Centre in NDE, grant EP/L022125/1.

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