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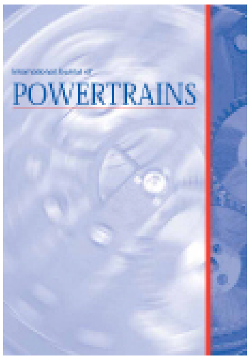

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Transmission energy consumption analysis using ridge regression in wireless sensor nodes

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Abstract: Wireless sensor nodes and its constitution of energy consumption in transferring sensory data to sink node results in a linear relationship. However, the quasi state of sensors makes over and under estimates of the communicating sensor data. This work proposes a 'ridge regression wireless data transfer rate' (RRWDTR) to interpret the energy analysis incorporating optimum route and its energy constituents, which relies on underlying resources. Since nodes are collocated to provide multi-hop communication, the independent variables of event generation are forwarding to a central node associated with sink results in multi-colinearity. The model thus deflates, leading to inaccurate estimates of prediction. RRWDTR uses structural relationship of the node and its resources using ridge regression incorporating characteristics of variance. Simulation of RRWDTR work has been done with penalty coefficient to predict near accurate estimates. Finally, comparison of RRWDTR has been done with linear regression wireless data transfer rate (LRWDTR).

Keywords: ridge regression; energy conservation.

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1 Introduction

Wireless sensor nodes and analysing the one way delay is an important function when describing a sensor reporting an event to the sink. In the case of wireless sensor actuator incorporated networks, roundtrip delay plays a major role where in the response time is critically determined. Utilisation of a node and link are important figures which satisfies the reporting status at appropriate intervals. Reliability is coined in as the probability in which task gets completed even in the scenario of hardware failure (Guo et al., 2014). The failure of sensor nodes with its past history and its reliability cost has been estimated in Wu et al. (2021). The execution time of a task and its failure rate are being considered with virtual sensors backing up the failure of physical sensors. Several works related to heterogeneity such as accessing network interfaces, computation power of nodes, channel model are augmenting factor for calculating efficacy. In Khan et al. (2021), control phase time and its associated reliability are characterised based on quality of service (QoS) into good, bad and poor metrics. Paired connectivity with GPS enabled to calculate the reference distance has been used to estimate the QoS.

Congestion control with discrete time modelling to alleviate bottleneck nodes using 'exponential reaching law' has been discussed in Qu et al. (2021). However, the pre-establishment delay by sensor and post establishment delay by actuator has not been considered. Determining the network centrality of a node in its path to sink has been done using a calculus approach. Embedding the graph via its computing power has been done by associating each data transfer moment and its cycle (Syarif et al., 2017). Mobile sensor nodes it is difficult to calculate the centrality measures as nodes relocate, changing the degree of association to its neighbours. The discussion based on partition has been done in 'geometric' and 'harmonic' centrality. The former consider geometric mean for calculating short paths and the latter considers reciprocal of arithmetic mean to remove outliers (Senturk, 2019). Closeness centrality with received signal strength indicator has been discussed with clustering for reducing localisation errors (Ahmad et al., 2018). Multi-criteria decision algorithm in Zheng and Yang (2021), with measurement method states the need of aggregation coefficient. Influencing factor calculated by actual edges, it is directly connected neighbours and the edges associated to the neighbour.

'Convergence theorem' is one among the suitable solutions in finding the best fit line and global minimum for a given slope. Linear regression provides best fit for training data but when scenarios of testing minimising the error requires multiple best fit lines. The Ridge regression plays a role wherein the unit change has been modelled to exploit over fitting of resource with communication sensors and its sink.

The concept of linear regression uses the least square error and its best fit. This works best when wireless resources and its matching characteristic of data transfer for training data. The model of linear regression incorporating least square error fails when either wireless resources such as bandwidth or the data transfer happens to vary stochastically. To overcome such effects, a ridge regression with generalisation capability is incorporated. It provides consistency by including a tolerance factor with wireless resources and sensor nodes data transfer and its variability.

The main highlight of this work is to build a model for exploiting the level of variance in wireless sensor and its resources for predictions of data transfer using Ridge regression.

Organisation of the paper Section 2 deals with related works considering network centrality, energy incurred its balancing features for wireless sensor nodes. Section 3 deals with proposed work on linear regression and ridge regression in wireless data transfer. Section 4 describes the simulation results attained with NS2 simulator to validate the proposed works. Section 5 concludes the overall work.

2 Related works

Taylor series provides insightful results in prediction when combined with ANN this has been discussed in Mangai et al. (2014). The non linear component in a Taylor series has been processed using ANN and the model produces better fitness values. Predicting sensor data and its energy consumption has been done in Anand and Titus (2017) via time series model. However, the model does not predict the non linear errors and is not suitable when back off in transmission occurs due to communication void.

Four centrality measures has been discussed in Gaitán et al. (2021), degree centrality denotes the single hop neighbour directly associated to a node. Closeness centrality denotes location proximity of node to other node in a network, mentioned via geo-disc distance. Betweenness centrality mentions the quantity of the shortest path passing along the network. Eigenvector centrality measures the networking of a particular node within the network. Optimal radius of clusters has been discussed in Ghosal et al. (2020)

considering the event of interest using convex optimisation method. The parameter of data flow within the cluster and lifetime of sensors requires network related information to specify the objective functions to solve convex optimisation problems.

Task allocation strategy has been discussed in Yang et al. (2020) based on the intimacy level of resources such as link quality and degree of node. It also avoids redundancy in reporting a task, whereas it associates nodes for appropriate task adjustment and reporting. In Park et al. (2017), closeness related centrality measure has been discussed with 'Lyapunov Krasovskii' function for providing robustness in delay. The synchronisation problem associated with coupling delay has been resolved by considering the centrality nodes with the inner and outer coupling coefficients (Park et al., 2017). Predicting the data transfer rate based on network wide synchronisations has been considered rather than centrality measure. The data transfer rate has been improved via localisation and resource prediction. Network wide synchronisation among nodes results in increasing the transfer rate, but reporting delay will also increase, decreasing the robustness (Anand et al., 2020). Trade off between coverage rate and connectivity has been discussed with whale optimisation algorithm. Based on the inertia weight, are being adjusted with cosine decreasing function to enable global and local search to improve convergence speed (Yue et al., 2021). Energy consumption by reducing unnecessary network reconstruction via local link repair have been done in Aghaei et al. (2021). The works of link restoration could be achieved in small, medium size network and is difficult for larger networks. Simultaneously, congestion also increases, whereby imposing number of retransmission and depleting energy.

Load balancing among links at different layers of topology provides better resilience of network lifetime. However, the work explores heterogeneous data in discriminating the energy imbalance scenarios considering predetermined packet sizes of such as audio and video (Zhang et al., 2020). Prolonging the network lifetime and reducing the quantity of relay nodes has been done using multi-objective optimisation problem. The optimisation technique finds the 'Nadir point' relating to maximum bound for both objectives such as network lifetime and relay quantity (Tam et al., 2021). Q-learning strategy has been discussed in He et al. (2020) to find the energy incurred and switching times. Time-critical application for sensor, the stochastic transition results in failure. Providing the shortest path in Saha et al. (2021) considering the edges and its existence probability has been done sampling method. It ensures that end to end accuracy in uncertain graphs. In Shukry (2021), stability of a node in terms of its local and global degree and its associated energy consumption has been discussed. Additionally, the number of times packet retransmission has been reduced by considered link quality and overhead, achieving energy balance. In Smys et al. (2021), path development streams a vital role in determine the energy efficiency rate for both time and event driven protocols. So performance indices of routing have to involve latency and energy consumption (Smys et al., 2021). Distance based communication with relay and centrality are widely used application in various vehicular networks. The ultimate aim of these networks is to achieve data flow rate with appropriate connectivity times (Dhaya and Kanthavel, 2021). Incorporating a penalty term in kernel regression with machine learning reduces the error distribution by limiting the weights. The model also attains stability in the presence of noise in visible light communication (Wu et al., 2020). Regression along with deep learning has been used to model the non linear relationship that exhibits in industrial sensors. The multivariate relationship between independent variables has found to be better in terms of prediction combining both the approaches (Vaila et al., 2021).

2.1 Problem description

In complex networks, the possibility of analysing the centrality measures has been given using ‘k core interconnection method’. That is the number of interconnection less than the threshold value is iteratively calculated and assigned such that core nodes with less interconnection has been removed (Dorogovtsev et al., 2006). The feasibility of incorporating ‘centrality’ is difficult as the wireless sensor nodes are mobile and also reutilisation of resources such as link quality depends on functionality of sensors. The process of identifying the link, nodes and finding the centrality measures is one of the most critical tasks. This centrality measures which will degrade the performance of network performance such as delay, throughput has to be mitigated.

3 Ridge regression wireless data transfer rate

The pre-processing step includes finding the feature selection via LASSO models and using ridge regression for shrinking the coefficient.

The ridge regression equation in equation (3) incorporates a penalty term and is always less than that of ‘line of best fit’ to minimise the over fitting of resource. Variables considered in this analysis uses event generation rate as independent variable whereas the ‘throughput’ and ‘delay’ as dependant variables.

Initially, linear regression is being performed to interpret the line of best fit using ‘least square regression’ for training the model. Further, the changes in unit slope and ridge regression coefficient are involved to minimise the variance.

The cost function and least square regression line have been given in equations (1) to (3) as below.

$$CF = \frac{1}{2m} \sum_{i=1}^{m} (\hat{s} - s)^2 \tag{1}$$

In equation (1), $\hat{s}$ indicates the line of best fit, ‘s’ indicates the actual sensor data point and m slope which is analogous to number of data points.

$$\hat{s} = lx + c \tag{2}$$

In equation (2), the line of best fit $\hat{s}$ is given by using slope ‘l’ and independent variable ‘x’ and constant ‘c’.

The process of switching from linear to ridge is determined by the factors of tolerance (T) in equation 3and variation inflation factor (VIF) as in equation (4).

$$T = 1 - R^2 \tag{3}$$

The value of R^2 is calculated as the square of correlation between $\hat{s}_i$ with remaining s.

$$VIF = \frac{1}{T} \tag{4}$$

Linear regression fails in the context of nonlinear sensory data. The objective of using linear regression is not meet in the context testing new sensory data leading to high error rate and increase in energy consumption.

The ridge regression line has been given in equation (5) as below.

$$CF = \frac{1}{2m}\sum_{i=1}^{m}(\hat{s}-s)^2 \times a \times (k)^2 \tag{5}$$

The value of '*a*' known as bias in equation (5) favours the dependant variable and ensures less sensitivity is given to independent variables. The *k* denotes the penalty coefficient to reduce the over fitting conditions. The '*a*' ranges from 0 to 1 and the serves to reduce the penalty coefficient of *k*.

The steep slope is iteratively reduced in this context by using suitable line of fit via ridge regression. Thus, the over fitting of sensory data and its unexpected increase in traffic has been resolved using retraining with suitable bias appropriate solution.

4 Results and discussion

Simulation parameters that influence the network design has been shown in Table 1. Network simulator 2 has been used in this work, incorporating BonnMotion generator (Aschenbruck et al., 2010). A conventional random waypoint incorporates 'pausing time' for a specific duration it waits known as pause time and then moves in its specified minimal and maximal speed. The process of incorporating BonnMotion generator attraction points which calculates distance which allows data characterisation.

Table 1 Significant simulation parameters and its values used

Parameter	*Value*
Terrain	1,000 m × 1,000 m
Mobility scenario generation	BonnMotion generator
Mobility model	Random waypoint
Number of nodes	100
Sinks	4
Initial energy	3 J
Transmit power	0.8 W
Receive power	0.3 W
Idle power	0.1 W
Simulation duration	1,000 s

The responsiveness of event in Figure 1 for latency in reporting packet for an event has been found to be less in the context of ridge regression wireless data transfer rate (RRWDTR) compared to linear regression wireless data transfer rate (LRWDTR).

Average waiting time of event in Figure 2 an event has been found to be less in the context of RRWDTR compared to LRWDTR.

The conceptualisation of increasing the number of packets in reporting an event states that the latency of reporting increases as packets are routed through logical neighbours. The problem might result in consecutive events are more likely to have larger reporting time resulting in failure of centrality metric.

The transmission energy of centrality nodes has been analysed with increasing event generation rate in Figure 3. As the event generation rate increases, the centrality nodes consume more energy. RRWDTR consumes less energy by providing efficient strategies overcoming the standard operating line of best fit measure used in ridge regression.

Figure 1 Packets per event versus latency (*s*) (see online version for colours)

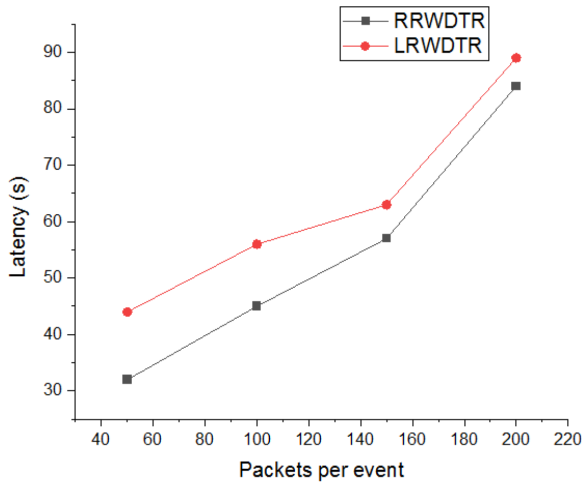
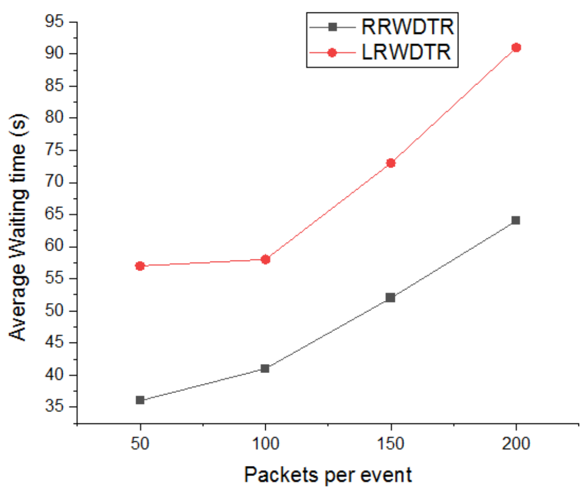


Figure 2 Packets per event versus average waiting time (*s*) (see online version for colours)



In different operating conditions of wireless sensor node and it resources, the transmission energy does not exploit a linear relationship. Hence, combination of linear features in predicting results in retransmission and involves more energy consumption, as in Figure 3. So the concept of Ridge regression prevents over fitting of sensor data and its resources by including penalty coefficient and suitable bias.

The recovery delay in Figure 4 indicates the reconstruction process where centrality of nodes gets drifted due to the incorporated mobility model. It is analogous to path reconstruction delay where centrality measure changes and network realign due to the response time of ridge regression coefficients.

Figure 3 Even generation rate versus transmission energy of centrality node (see online version for colours)

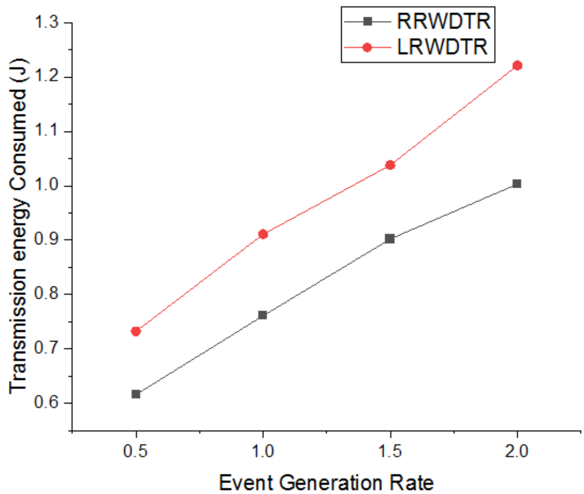
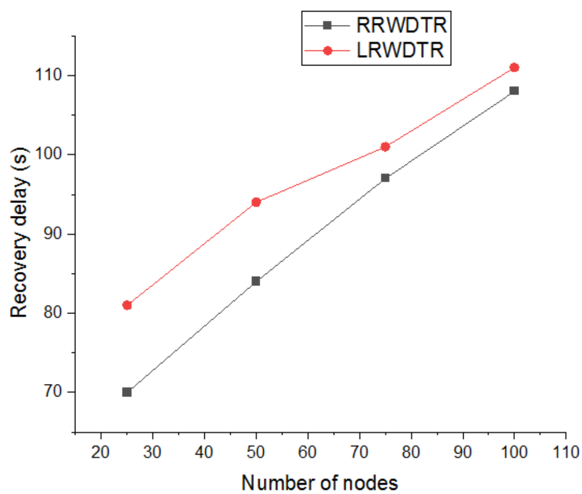


Figure 4 Recovery delay versus number of nodes (see online version for colours)



The concept of low bias and low variance is being incorporated in the 'RRWDTR' provides generalisation capability. There prevails a steep slope for a unit increase in event generation rate with energy consumption in context resulting in higher transmission energy for LRWDTR. In the context of RRWDTR steep slope for a unit increase in event generation rate with energy consumption is penalised which reduce the errors as the number of iteration increases resulting in reduced transmission energy.

5 Conclusions

The wireless sensor nodes influenced by a high variance in topological coordination due to mobility and deviation in sensory data transfer rate has been regularised using RRWDTR. The over fitting of sensory data will lead to increase in retransmission, which has been tuned to provide proper limiting bounds. Thus, the process of calculating sensory data transfer under a wireless stochastic environment has been found to be better when modelled with variance incorporating penalty term. Future work would deal in resilience of a network to errors in temporal connectivity, which further improves the penalty coefficient in ridge regression.

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