TATA CONSULTANCY SERVICES

MACHINE LOAD ESTIMATION VIA STACKED AUTOENCODER REGRESSION

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MOTIVATION

- To estimate axial and spindle load in a Computer Numerical Control machine from input sensor readings like spindle speed, feed rate, surface speed etc. – *a standard regression problem.*
- To develop a data driven approach for load estimation as an alternative to physics based models, which is not always feasible due to complicated manufacturing systems dynamics.
- To learn arbitrary relationships between the load and sensor readings.

PROPOSED APPROACH

- Incorporated a regression model based on the Stacked Autoencoder framework with ***joint learning*** of encoder-decoder and regression weights in a more optimal fashion, instead of greedy layer wise training in two phases.
- Regression model built on top of an asymmetric autoencoder architecture to reduce overfitting.
- Formulated a ***joint optimization problem*** and solved it using a variable splitting Augmented Lagrangian approach.

Methodology

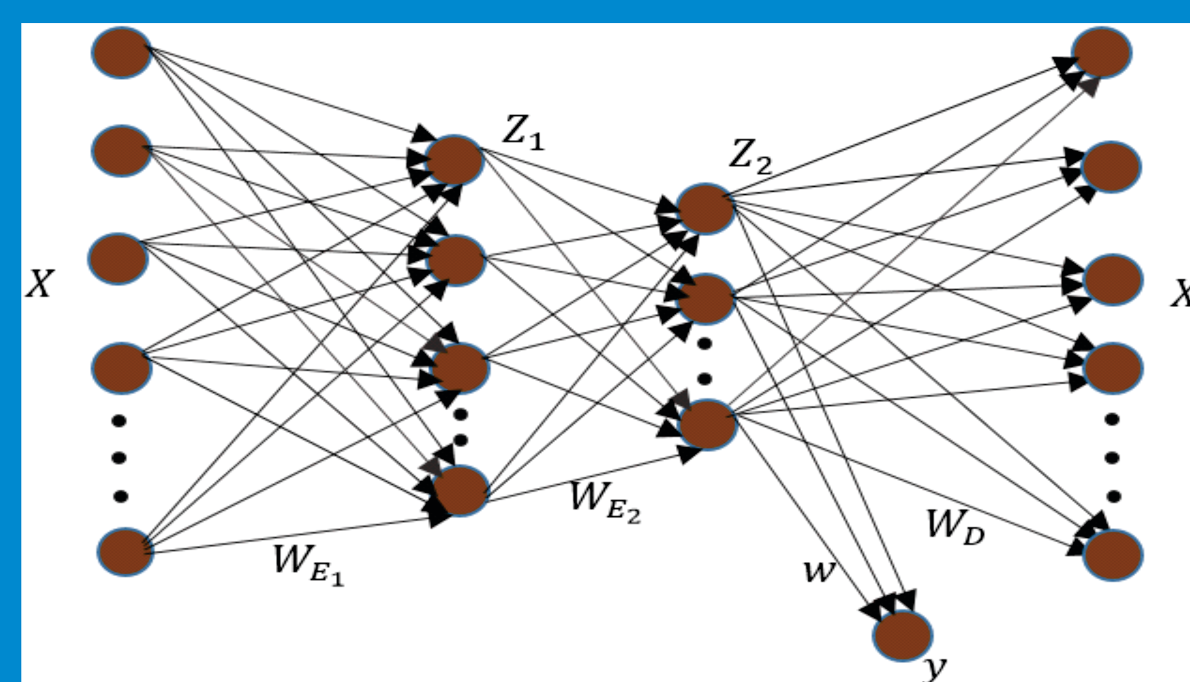
Step 1: *Proposed regression model is formulated as non-convex joint optimization function,*

$$\underset{W_{E_1},W_{E_2},W_D,w}{argmin}\left(\begin{array}{c}\left\|\left(X-W_D\varphi\left(W_{E_2}\varphi(W_{E_1}X)\right)\right)\right\|_F^2\\ +\lambda\left\|y-w^T\varphi\left(W_{E_2}\varphi(W_{E_1}X)\right)\right\|_F^2\end{array}\right) \quad (1)$$

Step 2: *Two proxy variables are introduced :*

$Z_2 = \varphi\left(W_{E_2}\varphi(W_{E_1}X)\right)$ and $Z_1 = \varphi(W_{E_1}X)$ *and the eq 1 is reformulated into corresponding Augmented Lagrangian formulation:*

$$\underset{W_{E_1},W_{E_2},W_D,w,Z_1,Z_2}{arg\,min}\left(\begin{array}{c}\|X-W_DZ_2\|_F^2+\lambda\|y-w^TZ_2\|_F^2\\ +\mu_2\left\|Z_2-\varphi(W_{E_2}Z_1)\right\|_F^2\\ +\mu_1\left\|Z_1-\varphi(W_{E_1}X)\right\|_F^2\end{array}\right) \quad (2)$$



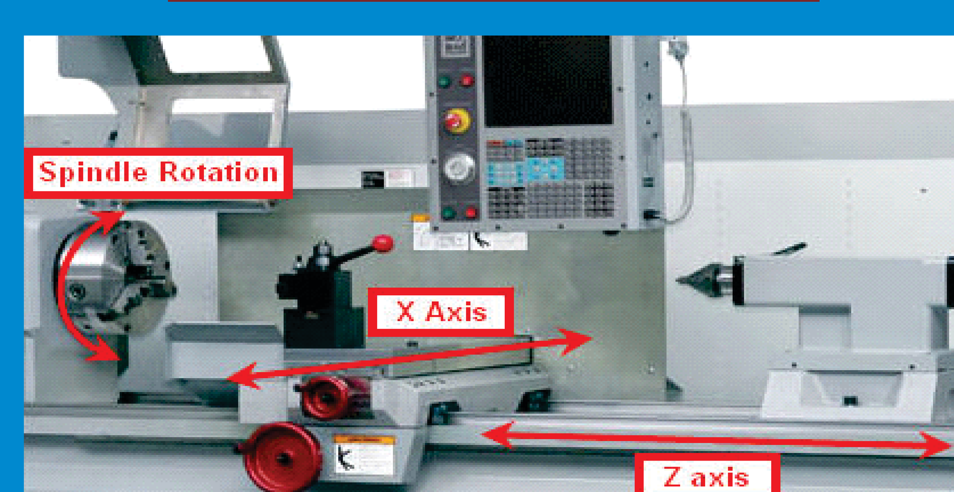
Architecture of the proposed Asymmetric Stacked Autoencoder for Regression

Step 3: *Equation 2 is broken into smaller sub-problems using Alternating Direction Method of Multipliers (ADMM) and the encoder-decoder and regression weights are learnt in multiple iterations. This concludes training.*

Step 4: *During testing, the unknown output $\tilde{y}$ for test data X_{test} can be estimated using the learned weights by solving*

$$\tilde{y} = w^T\varphi\left(W_{E_2}\varphi(W_{E_1}X_{test})\right)$$

EXPERIMENTS AND RESULTS



A CNC turning machine

Axes names	λ	μ_1	μ_2
Axis 1	1.6	1.3	1.3
Axis 2	0.5	1.7	1.7
Axis 3	0.6	1.6	1.6
Axis 4	1.1	1.5	1.5
Spindle	0.7	1.6	1.6

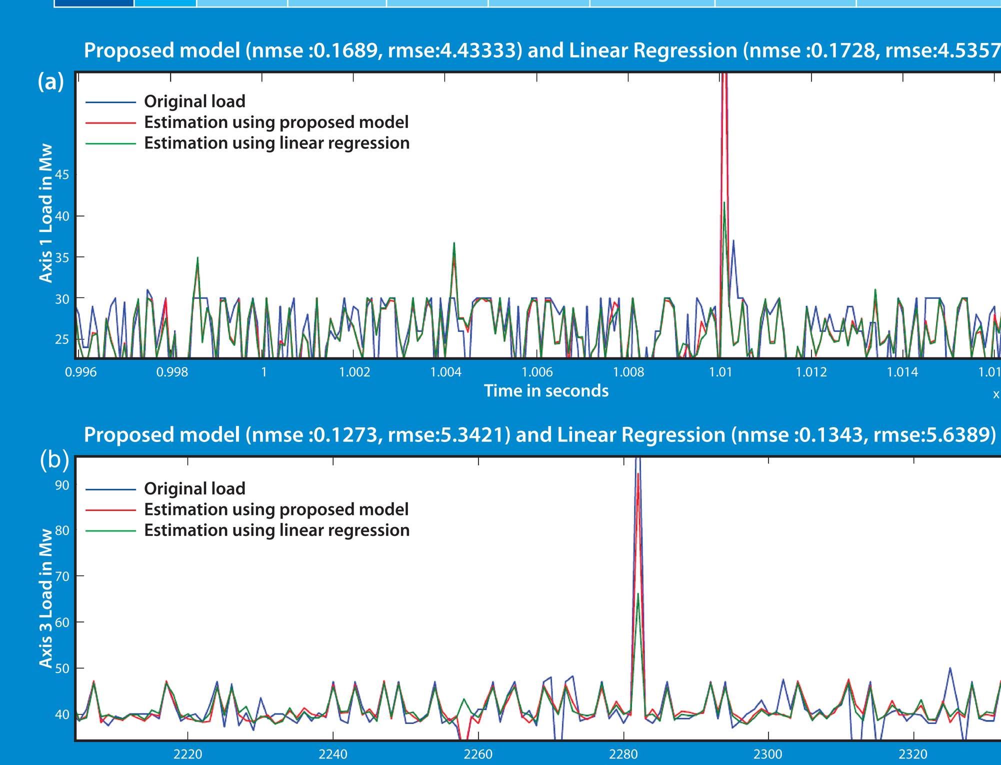
Parameter values considered for experiments using the proposed regression model

Performance metrics:

$$NMSE = \frac{\|y-\tilde{y}\|_2}{\|y\|_2}$$

$$RMSE = \sqrt{\frac{\sum_{m=1}^{N}(y_m-\tilde{y}_m)^2}{N}};\ N = length(y)$$

Day	Axis	Perf. metric	Linear Regression	LASSO	SVR-Polynomial	SVR-Gaussian	Traditional SAE	Regression using model proposed
4-Apr	Axis 3	NMSE	0.1208	0.1231	0.1307	0.1308	0.1204	**0.1162**
		RMSE	5.0349	5.1313	7.0871	7.0864	5.0163	**4.8417**
4-Apr	Axis 4	NMSE	0.8018	0.8026	0.9593	0.9717	0.98	**0.6579**
		RMSE	4.9956	5.0007	6.188	6.1863	6.1061	**4.0995**
7-Apr	Axis 1	NMSE	0.6343	0.6353	0.6841	0.6852	0.7132	**0.5842**
		RMSE	5.1879	5.1959	6.1761	6.1635	5.8331	**4.4397**
7-Apr	Spin-dle	NMSE	0.8675	0.8806	0.9978	0.999	0.9809	**0.8141**
		RMSE	7.1641	7.2726	8.2515	8.2523	8.101	**6.7231**
12-Apr	Axis 3	NMSE	0.1082	0.1082	0.1168	0.1185	0.1026	**0.1001**
		RMSE	4.4554	4.4554	6.0906	6.0639	4.2260	**4.1199**
12-Apr	Axis 4	NMSE	0.7401	0.7591	0.9601	0.9806	0.9862	**0.5372**
		RMSE	4.8051	4.9286	6.4675	6.4629	6.4030	**3.4877**



a) Load in axis 1 on 17 Apr (b) Load in axis 3 on 17 Apr

Observations

- Consistent improvement in performance compared to other techniques.
- Signal peaks could be better estimated using the proposed model.
- The model can be used for any regression problem.

REFERENCES

[1] D.Y. Pimenov, "Mathematical modeling of power spent in face milling taking into consideration tool wear," Journal of Friction and Wear, vol. 36, no. 1, pp. 45–48, 2015.

[2] Y. Bengio, P. Lamblin, D. Popovici, and H. Larochelle, "Greedy layer-wise training of deep networks," in Advances in neural information processing systems, 2007, pp. 153–160.

[3] A. Majumdar and A. Tripathi, "Asymmetric stacked autoencoder," in Neural Networks (IJCNN), 2017 International Joint Conference on. IEEE, 2017, pp. 911–918.

[4] K.O. J¨ornsten, M. N¨asberg, and P.A. Smeds, "Variable splitting: A new Lagrangean relaxation approach to some mathematical programming models", University of Link¨oping, Department of Mathematics, 1985.