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AN ARTIFICIAL NEURAL NETWORK APPROACH TO PAYLOAD ESTIMATION IN FOUR WHEEL DRIVE LOADERS

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ABSTRACT

Estimation of the manipulated payload mass in off-highway machines is made non-trivial by the nonlinearities associated with the hydraulic systems used to actuate the linkage of the machine in addition to the nonlinearity of the kinematics of the linkage itself. Hydraulic cylinder friction, hydraulic conduit compressibility, linkage machining variation and linkage joint friction all make this a complex task under even ideal (machine static) conditions. This problem is made even more difficult when the linkage is mobile as is often the case with off-highway equipment such as four-wheel-drive loaders, cranes, and excavators. The rigid body motion of this type of equipment affects the gravitational loads seen in the linkage and impacts the payload estimate. The commercially available state-of-the-art load estimation solutions rely on the mobile machine becoming pseudo-static in order to maintain accuracy. This requirement increases the time required to move the material and decreases the productivity of the machine. An artificial neural network solution to this problem that enables the machine to remain dynamic and still accurately estimate the payload is discussed in this paper. Development and implementation on an actual four-wheel-drive loader is shown.

INTRODUCTION

A primary application for four-wheel-drive loaders is manipulating various forms of aggregate. This typically takes one of two task forms. The first is stockpiling where some amount of material is moved from one location in a quarry to another location. The second is truck loading where some amount of material is loaded by the four-wheel-drive loader into a truck used for on-highway transportation. In the truck loading application, the amount of material placed in the dump box of the on-highway truck is critical. The governing departments or ministries of transportation in the states or provinces where the on-highway trucks are traveling govern the load limit the trucks may carry legally without incurring financial penalty. These limits are enforced to increase longevity of the road surfaces. It is advantageous to the finances of the trucking operation to maximize the truck payload while not exceeding the weight limits for the truck. To this end, large weighing scales are utilized at the exit of the quarries to weigh all trucks leaving for on-highway use. If the trucks weigh over their maximum limit, they must return to the quarry floor where they must unload some of the aggregate before proceeding. If they unload too much weight, the loader must add aggregate back to the truck in an attempt to maximum the truck's payload. This is a tedious task that can take significant time which utilizes a significant amount of fuel which negatively affects the financial performance of the quarry. To solve this dilemma, on-board weighing scales started being developed nearly fifteen years ago. The scale mounted to the four-wheel-drive loader utilizes hydraulic pressure in the main lift cylinders to estimate the payload in the bucket. The four-wheel-drive loader scale then weighs the material in the four-wheel-drive loader bucket. When the four-wheel-drive loader dumps the bucket of material in the truck the mass of material in the truck is known. This enables the truck to weigh at the exit scale with confidence that the truck load is optimized to the legal limit.

The state of the art for four-wheel-drive loader scales is worth describing to understand why the work presented in the paper is of use. The current state of the art for a typical four-wheel drive loader scale typically requires the machine to come to some pseudo-static equilibrium before and accurate measurement can be taken. This requires the machine operator to decelerate the machine and then accelerate again to reach the truck. This disruption in the work cycle uses energy that could be eliminated if an accurate dynamic measurement was possible. Additionally, if the weight of the material being carried by the mobile equipment is too much to complete a truckload under the legal limit, the operator must dispose of some material and re-weigh. The re-weigh operation, while possibly not being eliminated, should require the minimum amount of consumed energy in order to be fuel efficient. A typical truck loading cycle for a wheel loader may take 40 seconds with five seconds being used to weigh the material. If the five seconds could be eliminated, the cycle time could be improved by 12.5% and the energy consumed reduced.

The thrust of this research work was to develop a weighing system/algorithm that delivers current state-of-the-art accuracy (+/-1% full scale) while the machine is operating in its normal dynamic cycle. The economic motivation behind this work is reducing the energy consumed by the vehicle and thus reducing the input fuel costs. The machine chosen for this research work is a Deere 644J 4WD loader as shown in Figure 1.

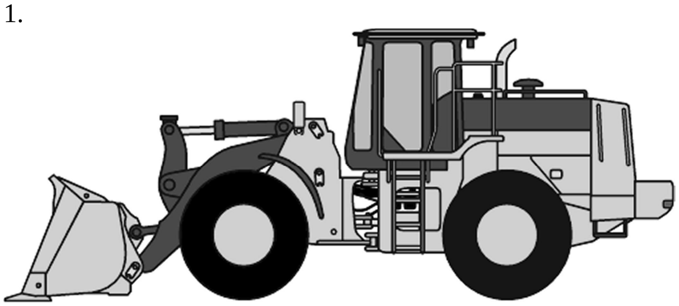

Figure 1: Deere 644J 4WD Loader

LITERATURE REVIEW

The topic of dynamic payload estimation and related work has created a small, but pertinent volume of research. Some of this research is involved with estimating kinematic parameters for linkages and actuators in preparation for developing a model-based payload estimation algorithm or for control purposes. Tafazoli et al [1] describe a method for estimating gravitational linkage parameters for an excavator and then use these estimated parameters in conjunction with load pins (i.e. instrumented joint pins capable of measuring joint forces) that the payload in the excavator bucket can be estimated to within 5% full scale. Similar work towards estimating gravitational and friction parameters in mobile linkages may also be found in [2][3].

Additionally, the topic of dynamic payload estimation has been researched significantly in applicable industries. Kyrtsos et al in [4] describe a method of estimating payload in a four-wheel-drive loader utilizing the lift cylinder pressures and linkage position. The method described relies on fitting a polynomial to the pressure information in order to smooth it out and provide a consistent payload estimate. This methodology is further refined in [5] and [6] with [6] describing the algorithm in entirety, presumably as implemented on wheel loaders described in the patent. The final algorithm adds correction factors for the velocity at which the lift was accomplished but is otherwise similar to the algorithm described in [4]. It should be noted that [6] claims that the algorithm can be utilized while the machine is moving, but this simply means while the lift is occurring, not rigid body motion of the entire vehicle.

The methodology developed in this paper is a continuation of the method developed in [7]. In [7], the methodology relied on an artificial neural network (ANN) trained using differential pressure across the boom cylinder, boom cylinder stroke, bucket cylinder stroke, boom cylinder velocity, and a kinematic model payload estimate. This algorithm was effective but produced an accuracy of 3.47% full scale which does not meet the requirement in the industry of +/- 1% full scale.

ALGORITHM

The original algorithm mentioned in [7], utilized a set of data that did not contain any information regardin ghte rigid body motions of the machine. This is a significant limitation of that methodology since the four-wheel-drive loader typically undergoes significant amounts of acceleration and deceleration in a typical work cycle as seen in Figure 2.

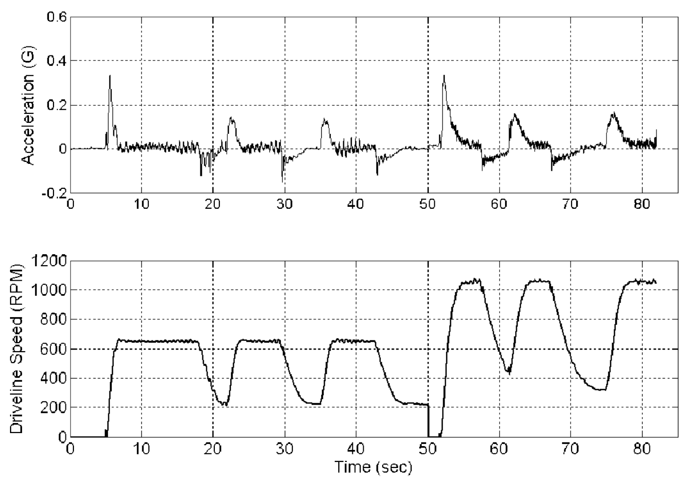

Figure 2: Acceleration During Transport

The acceleration and deceleration of the vehicle has the affect of accelerating and decelerating the payload in the four-wheel-drive loader bucket. This in turn has the affect of increasing and decreasing the boom cylinder pressure differential. This can bee seen in the boom pressure differential data shown in Figure 2 for a four-wheel-drive loader transporting across a typical quarry floor.

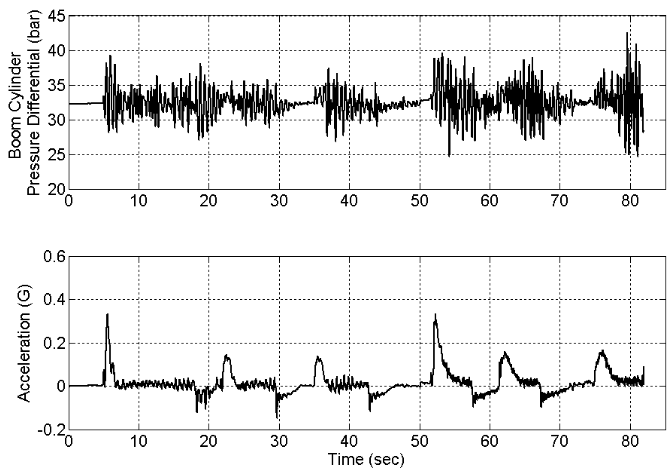

Figure 3: Boom Pressure Differential During Transport

Because of this limitation, the algorithm in [7] was modified to incorporate acceleration data. The accelerometer was mounted in the front frame that the loader linkage seen in Figure 3 attaches to. This accelerometer data was collected in both the X and Y direction as defined in Figure 4.

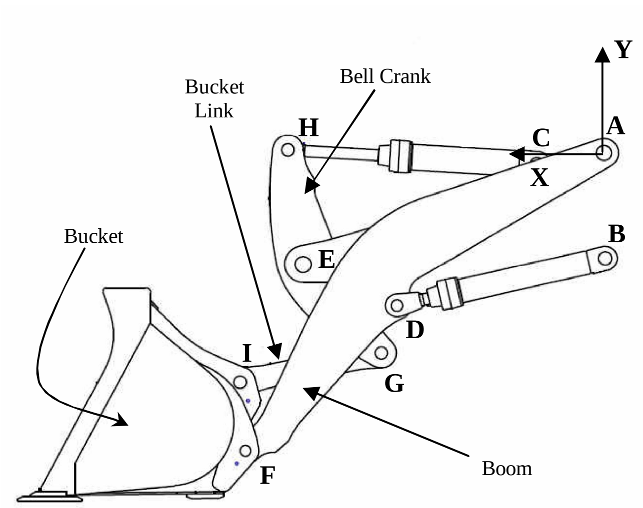

Figure 4: Four-Wheel-Drive Loader Linkage

A data set was collected from an actual John Deere 644J four-wheel-drive loader. This data set included differential pressure across the boom cylinder, boom cylinder stroke, bucket cylinder stroke, and X-direction acceleration. The data was then utilized with the kinematic model developed in [7] to calculate the payload estimate from the collected data using the kinematic model. This calculated estimate was then utilized along with the differential pressure across the boom cylinder, boom cylinder stroke, bucket cylinder stroke, and X-direction acceleration for training a 5x10x10x1 ANN. Only half of the data set was used for training while the other half was held for later testing of the accuracy of the algorithm. The ANN topology and input/output relationship is seen in Figure 4 (no network weights or biases are shown for sake of clarity.

The feed forward network in Figure 5 was trained using the Levenberg-Marquardt training algorithm. The data used for training consisted of two separate runs for three different payloads. One of the two runs was collected while driving the four-wheel-drive loader across a quarry floor while not manipulating the boom or bucket. The second run was collected while the boom was manipulated up and down. The three different payloads were 0 kg, 3945 kg, and 5563 kg.

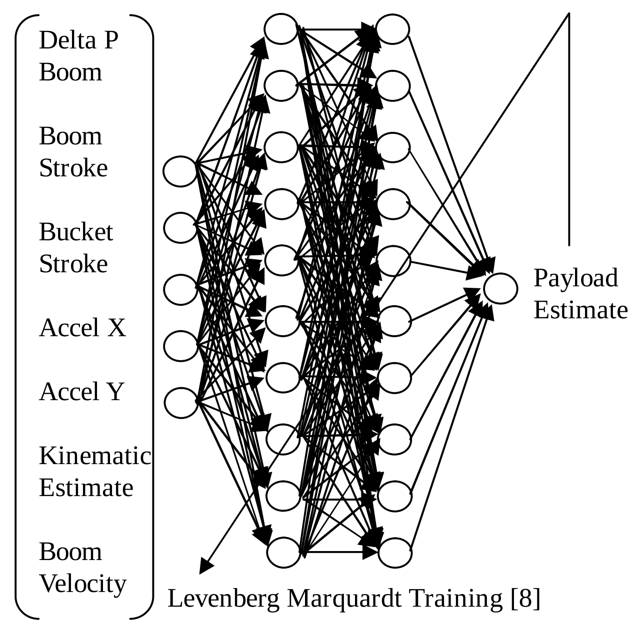

Figure 5: ANN topology

The network shown in Figure 5 was trained using the Levenberg-Marquardt algorithm on half of the data collected off the 644J four-wheel-drive loader. The results of this are shown in Figure 6.

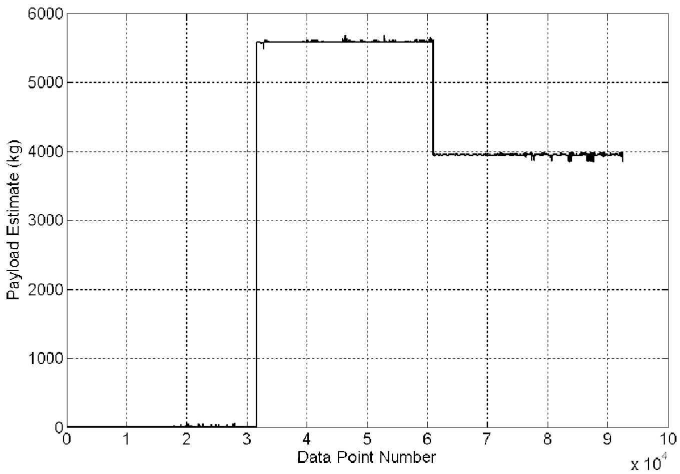

Figure 6: ANN Training Results

The numerical results of the training shown in Figure 6 give a payload estimate of .879 +/-94.92 kg for the zero load case (i.e. 0 kg payload), 5581.6 +/- 24.54 kg for the full load case (i.e. 5563 kg payload) and 3947.6 +/- 41.49 kg for the half load case (i.e. 3945 kg payload) at a 95% confidence interval. This gives a maximum error in training of 95.8 kg with a 95% confidence interval. This error should be compared to the maximum allowable of 1% full scale giving +/-55.81 kg. It can be seen that this algorithm does not meet the maximum allowable error at the zero load case, but does at the other two load cases for the training results.

The network shown in Figure 5 was then exercise by utilizing the other half of the data collected from the 644J four-wheel-drive loader that the network was not trained with. This simulation revealed that the network, when subjected to new data, performed slightly worse than on the data it had been trained with. The results from this exercise showed that the payload estimate at the zero load case was 1.3 +/- 109.3 kg, 5588.2 +/- 33.9 kg for the full load case and 3946.7 +/- 38.1 kg for the half load case. As in the training data, the worst case error occurred at the zero load condition giving an error of 110.6 kg for a 95% confidence interval. This should be compared to the maximum allowable error of 55.81 kg. The maximum error seen with this algorithm is nearly twice of the acceptable error. It is interesting to note that the deviation of the estimate decreases as the payload weight increases in general. It is believed this is due to the reduced impact of rigid body accelerations on the boom pressures relative to the impact caused by the actual payload.

It has been shown that including the acceleration information in the ANN algorithm, the worst case payload estimate is +/-1.96% full scale error. While this is not acceptable for the industry, it does represent a significant improvement over the +/-3.47% shown in [7].

FUTURE WORK

Because the ANN approach to payload estimation shown in this paper shows promise in being able to produce an accurate payload estimate under truly dynamic machine operating conditions further refinement of the algorithm will continue. Towards this end, efforts will be made to improve the algorithm by improving fidelity of the pre-filtering the training data undergoes before being used by the ANN. Additionally, size and topology of the ANN will be investigated to determine minimum size of the network required for accurate results.

The most important part of the future work in developing this algorithm will be to determine additional inputs to improve the fidelity of the results of the algorithm. Due to the computational overhead of the kinematic model calculation, effort will be given towards investigating new inputs such as driveline speed and engine speed in conjunction with the acceleration data in an attempt to remove the kinematic model data and calculation from the network inputs altogether.

NOMENCLATURE

ANN: Artificial Neural Network

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REFERENCES

[1] Tafazoli S., Lawrence, P.D., Salcudean S.E., Chan D., Bachmann S., and de Silva C.W., *Parameter Estimation and Actuator Friction Analysis for a Mini Excavator*, Proceedings of IEEE International Conference on Robotics and Automation. pp. 329-334. April 1996.

[2] Zweiri Y.H., Seneviratne L.D., and Althoefer K. *Parameter Estimation for Excavator Arm Using Generalized Newton Method*, IEEE Transactions on Robotics. Vol. 20, No. 4. pp. 762-767. August 2004.

[3] Tafazoli S., Lawrence P., and Salcudean S., *Identification of Inertial and Friction Parameters for Excavator Arms*, IEEE Transactions on Robotics and Automation. Vol. 15, No. 5. pp. 966-971. October 1999.

[4] Kyrtsos C., and Worrell D., *Dynamic Payload Monitor*, United States Patent 4,919,222. April 24, 1990.

[5] Kyrtsos C., and Worrell D., *Dynamic Payload Monitor*, United States Patent 5,070,953. Dec 10, 1991.

[6] Kyrtsos C., *Dynamic Payload Monitor*, United States Patent 5,105,896. April 21, 1992.

[7] Hindman J., Burton R., and Schoenau G., Payload Estimation in Four Wheel Drive Loaders, Transactions of the Tenth Scandinavian International Conference on Fluid Power. May 21, 2007.

[8] Hagan, M.T. & Menhaj, M. *Training Feed Forward Networks with the Marquardt Algorithm*. IEEE Transactions on Neural Networks. Vol. 5(6). pp. 989993.