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Hi Dr. Louw,

I managed to speak with the plant manager at Wellington site. He informed me that the RDX explosives plant is the newest and generates the most data. This is based on the Woolwich (Direct Nitration) process.

The general process involves:

1. Generating a nitrating acid ( $\text{HNO}_3$  and  $\text{H}_2\text{SO}_4$ )
2. Nitration (of hexamine)
3. Filtration, washing and neutralization
4. Crystallization

I was generally thinking of a project something along the lines of ... *"The use of Deep Learning to predict/warn/prevent off-spec key properties in exit streams"*. These 3 main exit streams of the plant are described below.

The prediction could focus on either a single stream or multiple streams. Or a single stream, taking the remaining 2 streams as inputs.

### **1. RDX Product**

Crystals, properties of interest:

- Purity (RDX)
- Particle size distribution
- Occluded acid content

The properties are influenced by nitration, filtration, washing and crystallization. Typically difficult to control, off-spec product generally cannot be re-worked and must be sent to the burning grounds which releases harmful combustion products.

### **2/3. Nitration Spent Acid & Waste Water**

The spent acid is generated in the nitration process and separated during primary filtration. The wash water is produced during washing and neutralization.

The main properties of interest are:

- Acid concentration
- Dissolved organic content

Variations in spent acid concentration causes damage to downstream tanks and processing equipment and can also affect the solubility of RDX, causing product losses. Organic content, dissolved RDX, can lead to unstable degradation and thermal runaway.

I'm not sure if they directly measure the organic content but I do know that they currently use excess chemical dosing than what is needed in a hit-or-miss kind of situation.

I am leaning towards RDX product, although, the frequency in which batch testing is done will determine how much data is available. Otherwise spent acid and waste water properties are easily measured and Rheinmetall will likely sponsor the sensors if they are not already installed.

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**Working Title** – “The application of Artificial Intelligence Deep Learning techniques for the prediction of key parameters in product output streams, control philosophy and pre-emptive action”

### **Background & Theme:**

Over the last few decades the amount of ever increasing availability of data is changing the way decisions are made in the manufacturing industry in areas such as scheduling, maintenance and quality control. Coupled with the exponential increase in capabilities of hardware, cloud-based architecture and algorithms, a new era of Smart Manufacturing (SM) or Industry 4.0 has begun. This new industrial revolution focuses heavily on interconnectivity and big data to enhance the relationship between smart digital technology and physical production for a holistic ecosystem.

Artificial intelligence, such as machine learning and deep learning techniques, enable predictions to be made based on pattern recognition and make decisions independently based on previous knowledge. The algorithms can be used to recognize relationships, derive generalizations and find new solutions or insight into complex processes. Application of these techniques to large amounts of data in manufacturing they have been established as a corner-stone of Industry 4.0.

### **Problem Statement:**

A major issue in the manufacturing industry - especially that of specialised complex chemicals – is quality control. Minor issues in the process may result in quality drops or variations in the final products which, in many cases, results in off-spec outputs that are unacceptable from a quality control perspective. This results in required re-work or complete disposal of product contributing heavily to costs, wastage, inefficiency and pollution.

In many complex systems with deeply embedded interactions of equipment and processing lines, traditional control systems as well as modelling can become highly complex. This is especially true in the explosives manufacturing industry which is a notoriously dangerous and difficult manufacturing field in which South Africa is currently one of the world-leaders.

Quality 4.0, a natural subset of Industry 4.0, focuses on the use of AI algorithms developed through machine learning to monitor and continually improve output quality by collecting usage and performance data from various sources. This data is consolidated and used to identify minor issues before they become more significant, boost efficiency and maintain high product quality.

South Africa is currently lagging behind the world in terms of Industry 4.0 adoption which could have severe impact on the future competitiveness in international markets, thus, investment into Industry 4.0 is crucial.

### **Literature:**

Machine learning and Deep learning techniques are being evaluated in many industries across the world with success.

### **Prediction of effluent concentration in a wastewater treatment plant using machine learning models**

Hon Guo et. Al, DOI: 10.1016/j.jes.2015.01.007

Two machine learning models were established to in order to predict 1-day interval total nitrogen (T-N) concentration of effluent resulting from a wastewater treatment plant in Korea. Water quality and meteorological data was used and the results showed that both models could be effectively applied with high prediction accuracy in both the training stage and validation stage.

### **Predictive Analysis of Water Quality Parameters using Deep Learning**

A. Solanki et. Al, DOI: 10.5120/ijca2015905874

Pollution of scarce water sources requires the careful monitoring of quality. Water quality data collected in India was used to in conjunction with deep learning techniques to provide accurate prediction of water quality parameters.

### **Water Quality Prediction Model of a Water Diversion Project Based on the Improved Artificial Bee Colony–Backpropagation Neural Network**

S. Chen et. Al, <https://doi.org/10.3390/w10060806>

Backpropogated neural network algorithms were tested against each other for the prediction and forecasting of water quality in to aid in pollution prevention. The resulting model shows high practicality for water quality prediction and can easily be applied in the field.

## **Project Plan**

The proposed project will attempt to apply the techniques of deep learning to an existing RDX manufacturing plant. Initially, a thorough understanding of the manufacturing process itself must be made. Thereafter, the development of an artificial intelligence algorithm will require a thorough understanding of theoretical deep learning concepts. The investigation will be broken down into phases (i) development and training (ii) validation (iii) evaluation.

RDX is one of the most widely manufactured explosives being used throughout the world, the manufacturing process is dangerous and, due to the volatile nature, material exiting the process must conform to strict quality specifications.

In this process key exiting material streams include the spent acid, waste water and RDX product itself. Key parameters for the spent acid and waste water streams include the acid concentration and dissolved organic content. RDX product must conform to strict purity, particle size distribution and occluded acid content specifications.

Variations in these parameters routines cause damage to downstream storage tanks, processing equipment and result in product losses or even burning of entire batches themselves – contributing to significant pollution production and costs.

These properties are influenced heavily by multiple operating parameters in the nitration, filtration, washing and crystallizing processes leading to difficult control.

Historical logging data from various steps in the process will be captured. This data, or a subset thereof, will be used to develop and train deep learning algorithms in layers to create an artificial neural network that can learn and make intelligent predictions on its own.

Once the training phase is complete, the resulting algorithm will be evaluated in the validation phase. This can be performed on both real-time data and/or remaining historical data not used in the training phase. Comparison will be made to determine accuracy relative to historical QA testing results.

Successful application of the algorithm to the process will aid in exploring the feasibility of implementing real-time monitoring and warnings on live data which could, in the future, be connected directly to control elements in the plant – making adjustments in real-time.

