Role of Artificial Intelligence in Industry 4.0 – Application to Indian Leather Industry

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• History of Industrial Evolution
• 4th Industrial Revolution
• Neural Nets & AI Techniques
• Cyber Physical Systems – Process data
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Digital India / Make-in-India Program

- India accounts for 12.93% of the world’s leather production of hides/skins.
- High Growth projected in the next five years.
- Indian leather industry has one of the youngest workforce with 55% of workforce below 35 years of age.
- India is the second largest producer of footwear and leather garments in the world.

**WHY FDI**

- **Strong Raw Material Base:** A strong base for raw materials – India is endowed with 20% of the world’s cattle and buffalo and 11% of the world’s goat and sheep population.
- India produces 2.5 billion sq. feet of leather, accounting for about 13% of global production.
- The Indian Leather Industry comprises of major segments namely Footwear, Finished Leather, Leather Goods, Leather Garments, Footwear Components and Saddlery and Harness. All these segments have high growth potential.
- Per capita consumption of footwear in India projected to increase up to 4 pairs and total domestic consumption is expected to reach up to 5 billion pairs by 2020.
- Great opportunity to set-up manufacturing facility of footwear components, considering increasing demand for fashion footwear in India.
The Advent of the 4th Industrial Revolution (IR) Age

4th Industrial Revolution

Components

Internet of Things
Cloud
Big data
Artificial Intelligence
Mobile

5G wireless network: 280 times faster than LTE and 70 times faster than 4G.

1st Industrial Revolution - 18th Century
Mechanization through steam engine

2nd Industrial Revolution 19th - 20th Century
Mass production through electric energy

3rd Industrial Revolution Late 20th Century
Intelligent Information Revolution through computer and internet

4th Industrial Revolution 21st Century

Intelligence Information Technology

Intelligence
Information
Big Data IoT Cloud

1st
Mechanization, water power, steam power

2nd
Mass production, assembly line, electricity

3rd
Computer and automation

4th
Cyber Physical Systems
Phases of Industrial Revolutions
-- A Journey through ages

1. 1760 to 1840 - Ushered in Mechanical production; railways and steam engine ← Industry 1.0

2. 1870 to 1940 - Mass production; electricity and assembly line ← Industry 2.0

3. 1960 to 2010 - Computers; semi conductors, main frame computing, personal devices, internet ← Industry 3.0
Watt’s Flyball Governor

1788 - Watt’s steam engine
Newcommen’s steam engine – a limited Success

Newcomen engines were successful in part because they were very safe to operate. Since the steam was under such low pressure (5 psi), there was no risk of a dangerous boiler explosion.

Power is supplied to the governor from the engine's output shaft by a belt connected to the flywheel. The governor is connected to a throttle valve that regulates the flow of steam supplying the prime mover. This in turn regulates amount of pressure acting on the piston. As the speed of the prime mover increases, the central spindle of the governor rotates at a faster rate and the kinetic energy of the balls increases. This allows the two masses on lever arms to move outwards and upwards against gravity. If the motion goes far enough, this motion causes the lever arms to pull down on a grooved collar, which moves a operating arm, which reduces the aperture of a throttle valve. The rate of working-fluid entering the cylinder is thus adjusted and the speed of the prime mover is settled in new position, preventing over-speeding or stalling the engine.
Mechanism

Watt’s governor
Analysis of James Clark Maxwell (1868)

\[ ml \ddot{\phi} = l(m\omega^2_G l \sin \phi \cos \phi - mg \sin \phi - b \dot{\phi}) \]

\[ J \dot{\omega}_E = k \cos \phi - T_L \]

\[ \omega_G = n\omega_E \]

**Linearization**

\[ \phi = \phi_0 + x \quad x << 1 \]

\[ \omega_E = \omega_G + y \quad y << 1 \]

\[ y + a_1 y + a_2 y + a_3 y = 0 \]
1885 Albert Butz invented Damper Flapper
- Bimetal Plate (Sensor/Control)
- Motor to move the furnace damper
* Started a company that became Honeywell in 1927

If room-temp is below set point
* Thermostat switching on makes the main motor shaft to turn one-half revolution opening the furnace's air damper.
  If room-temp is above set point
* Thermostat switching off makes the motor to turn another half revolution, closing the damper and damping the fire

* On-off control based on threshold

Home heating loop
Analog - Devices
1930’s Feedback Amplifire

- Signal amplification in first telecom systems (telephone)
  Analog vacuum tube amplifier technology
  * Feedback concept

- Bode analysis of transients in amplifire in 1940

\[
\frac{V_1 - V}{R_1} = \frac{V - V_2}{R_2}
\]

\[
V_2 = GV
\]

\[
\frac{V_1}{V_2} = R_1 \left[ \frac{1}{R_2} - \frac{1}{G} \left( \frac{1}{R_1} + \frac{1}{R_2} \right) \right] = -\frac{R_1}{R_2} \left[ 1 - \frac{1}{G} \left( 1 + \frac{R_2}{R_1} \right) \right]
\]
## 1940-World War II Military Applications

- **Sperry Gyroscope Company** – flight instruments – later bought by Honeywell to become Honeywell aerospace control business.

- **Servosystem** – gun pointing, ship steering, using gyro

- **Norden bombsight** – Honeywell’s C-1 autopilot – over 110,000 manufactured. (also participated in Iraq war, 2003)

* Concepts – electromechanical feedback, PID control.

- **Nyquist, servomechanism, transfer function analysis** – *System Stability*

---

Since it was quite tiresome to fly an unstable aircraft (Right’s Brother, 1905), there was strong motivation to find a mechanism that would stabilize an aircraft. Such a device, invented by Sperry, was based on the concept of feedback. Sperry used a gyro-stabilized pendulum to provide an indication of the vertical. He then arranged a feedback mechanism that would pull the stick to make the plane go up if it was pointing down and vice versa. The Sperry autopilot is the first use of feedback in aeronautical engineering.
1960’s Rocket Science

- SS-7 missile range control
  - through the main engine cutoff time

Range:
\[ r = F(\Delta V_x, \Delta V_y, \Delta x, \Delta y) \]

Range Error:
\[ \delta r(t) = f_1 \Delta V_x(t) + f_2 \Delta V_y(t) + f_3 \Delta x(t) + f_4 \Delta y(t) \]

Algorithm:

Track \( \delta r(t) \) Cut the engine off at \( T \) when
\[ \delta r(t) = 0 \]
MOTIVATION FOR AI

- Spurring AI-based innovation and establishing AI-ready infrastructure are necessary to prepare India’s jobs and skills markets for an AI-based future and to secure its strategic interests. - S. S. Vempati

- Recent advances in artificial intelligence (AI) are a wake-up call to policymakers in India.

- Industry 4.0, a German initiative, aims on optimization through AI and use of IoT, data analytics, additive manufacturing giving a shape of smart Industry. Cyber-physical systems monitor physical processes.
In leather processing, control and automation for recipes, heating, machining, robotic vacuums, and remote monitoring can be achieved by IoT.
Methods
(net-working & Data exchange)

Physical systems
- electronic sensors
- actuators
- digital devices

Automatic identification
smart objects
- wireless
- data analytics
- machine learning

Internet-of-Things

Trans-disciplinary obj
- cybernetics
- mechanical engg,
- mechatronics
- design
- Process science
- manufacturing sys
- comp sci

Control algorithms
computation AI

Cyber-physical-sys

Cloud computing
- on-demand self service
- network access
- resource pooling
- rapid elasticity
- measured service

Deploy Models:
public, private, community, hybrid

Delivery model:
- software based
- platform based
- infrastructure

Big data analytics
- Volume of data
- Variety of Data
- Velocity of generation of new data & analysis
- Value of data

Works on:
- Statistical modeling
- Optimization

Provides:
- process or product faults, threats in production systems, prediction of new issues in a production process

This tool helps in minimizing budget and data can be accessed easily. After water, electricity, gas and phone, cloud becomes the fifth utility for any industry.
Neural Networks

Biological Analogy

Dendrites

Axon

Synapses

Nodes

Synapses (weights)

Impulse
Behaviour of an artificial neural network to any particular input depends upon:

- **structure of each node (activation function)**
- **structure of the network (architecture)**
- **weights on each of the connections**
- **Non linear, parameterized function with restricted output range**

Mathematically, the output $y$ of a neural network can be expressed as:

$$ y = f \left( w_0 + \sum_{i=1}^{n-1} w_i x_i \right) $$
Neural Networks

- A mathematical model to solve engineering problems
  - Group of highly connected neurons to realize compositions of non linear functions

- Tasks
  - Classification
  - Discrimination
  - Estimation

- Types of networks
  - Feed forward Neural Networks
  - Recurrent Neural Networks
    - Hebbian networks: reward ‘good’ paths, punish ‘bad’ paths
    - Bayesian – deals with probability: the distribution of the neural network parameters is learnt
  - Support Vector machine - the minimal representative subset of the available data is used to calculate the synaptic weights of the neurons
Feed Forward Neural Networks

- The information is propagated from the inputs to the outputs.
- Computations of No non linear functions from $n$ input variables by compositions of $N_c$ algebraic functions.
- Time has no role (NO cycle between outputs and inputs).

- 3 types of learning
  - The supervised learning
  - The unsupervised learning
  - Reinforcement Learning
Learning in a Simple Neuron

\[ y = f\left[\sum_{i=0}^{2} w_i x_i \right] \]

where \( f(a) \) is the step function, such that:
\[
\begin{align*}
  f(a) &= 1, \quad a > 0 \\
  f(a) &= 0, \quad a \leq 0
\end{align*}
\]

\( H = \{W \mid W \in \mathbb{R}^{n+1}\} \)

"Full Meal Deal"
The Back-propagation Algorithm

On-Line algorithm:

1. Initialize weights
2. Present a pattern and target output
3. Compute output: \[ o_j = f\left[\sum_{i=0}^{n} w_{ij} o_i\right] \]
4. Update weights: \[ w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij} \]

where \[ \Delta w_{ij} = -\eta \frac{\delta E}{\delta w_{ij}} \]

Repeat starting at 2 until acceptable level of error
## Past Research & Literature

### History of Artificial Neural Networks

<table>
<thead>
<tr>
<th>Event</th>
<th>Year</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td><strong>Creation:</strong></td>
<td>1890</td>
<td>William James - defined a neuronal process of learning</td>
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<td><strong>Promising Technology:</strong></td>
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<td>1943: McCulloch and Pitts - earliest mathematical models</td>
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<td>1954: Hebb and IBM research group - earliest simulations</td>
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<td></td>
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<td>1958: Frank Rosenblatt - The Perceptron</td>
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<td><strong>Disenchantment:</strong></td>
<td>1969</td>
<td>Minsky and Papert - perceptrons have severe limitations</td>
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<tr>
<td><strong>Re-emergence:</strong></td>
<td>1985</td>
<td>Multi-layer nets that use back-propagation</td>
</tr>
<tr>
<td></td>
<td>1986</td>
<td>PDP Research Group - multi-disciplined approach</td>
</tr>
<tr>
<td></td>
<td>1986</td>
<td>Rumelhart, Hinton + Williams present backpropagation</td>
</tr>
<tr>
<td></td>
<td>1989</td>
<td>Tsividis: Neural Network on a chip</td>
</tr>
</tbody>
</table>
AI Development

- Artificial Intelligence (1950s) – Giving intelligence to machine
- Machine Learning (1980s) – realizing artificial intelligence (speech recognition, image recognition, playing go, dialogue)
- Deep Learning (2006) – for machine learning for higher prediction accuracy
  - A powerful class of machine learning model
  - Modern reincarnation of artificial neural network
  - Collection of simple, trainable mathematical functions
AI Development

- 1958: Rosenblatt’s Perceptron algorithm
- 1969: Minksky showed Perceptron could not solve the XOR problem, connectedness, parity.
- 1986: Rumelhart developed Backpropagation algorithm to train neural network
- Mid 90’s: Cortes and Vapnik published paper on Support Vector Machines
- 2006: Hinton and Salakhutdinov proposed using Restricted Boltzmann Machine for pre-train Deep Neural Network
AI Development

- 2007: Fei-Fei Li’s ImageNet assembling a database of 14 million labeled images (Data drives learning)
- 2011: Microsoft explored Speech recognition and IBM’s Watson
- 2014: Google acquired DeepMind, combining deep learning and reinforcement learning
- 2016: DeepMind’s AlphaGo defeated world champion Lee Sedol
Types of Learning

**Supervised**: Learning with a labeled training set
Example: email *classification* with already labeled emails

**Unsupervised**: Discover patterns in unlabeled data
Example: *cluster* similar documents based on text

**Reinforcement learning**: learn to act based on feedback/reward
Example: learn to play Go, reward: *win or lose*

Classification

Anomaly Detection

Sequence labeling

Regression

Clustering

Training

Sample labeled data (batch) → Forward it through the network, get predictions → Back-propagate the errors → Update the network weights

Optimize (min. or max.) objective/cost function $J(\theta)$
Generate error signal that measures difference between predictions and target values

Use error signal to change the weights and get more accurate predictions
Subtracting a fraction of the gradient moves user towards the (local) minimum of the cost function

Most Deep Networks use ReLU nowadays

- Trains much **faster**
  - accelerates the convergence of SGD
  - due to linear, non-saturating form
- Less expensive operations
  - compared to sigmoid/tanh (exponentials etc.)
  - implemented by simply thresholding a matrix at zero
- More **expressive**
- Prevents the **gradient vanishing problem**
A machine learning subfield of learning **representations** of data. Exceptional effective at **learning patterns**.
Deep learning algorithms attempt to learn (multiple levels of) representation by using a **hierarchy of multiple layers**
If you provide the system **tons of information**, it begins to understand it and respond in useful ways.
Deep Learning
Neutral Network

Deep Learning
- Nonlinear activation function
- Neuron could connect to every input
- Multi-levels with millions neurons
- Any function can be computed

Types of Deep Learning
- Deep Convolution
- Deep Boltzmann Machine
- Recurrent Neural Net
- New models and algorithms

Neural Network: pattern recognition or data classification

Big data (with large dataset)
L2 = weight decay

- Regularization term that penalizes big weights, added to the objective
- Weight decay value determines how dominant regularization is during gradient computation
- Big weight decay coefficient $\rightarrow$ big penalty for big weights

$$J_{reg}(\theta) = J(\theta) + \lambda \sum_k \theta_k^2$$

Early-stopping

- Use validation error to decide when to stop training
- Stop when monitored quantity has not improved after $n$ subsequent epochs
- $n$ is called patience

Regularization

Dropout

- Randomly drop units (along with their connections) during training
- Each unit retained with fixed probability $p$, independent of other units
- Hyper-parameter $p$ to be chosen (tuned)

Artificial Intelligence –
Deep Learning and its applications

- Information retrieval (search engines)
- Pattern recognition
- Audience targeting
- Sentiment analysis (based on written text)
- Personalization
- Automation
- Natural Language Processing
- Social media mining
- Organic search and content performance
- Brand and product differentiation

Data Centres
- Increase its energy efficiency by 15%
- 120 different variables (sensors, temperature gauges, fans, windows...)

- Trend Prediction
- Recognition
- New Knowledge
- Making Sense
- Replacing Human
Artificial Intelligence –
Deep Learning and its applications

- Language Translation
- Speech Recognition
- Generating Handwriting
- Face Recognition
- Autonomous Driving
- Generating Arts
- Imitating Famous Painters
- Generating Music
- Generating Photos

Power Systems
- Peak Load Forecast (e.g. Maximum Demand)
- Failure Prediction (e.g. Battery)
- Condition Monitoring (e.g. Partial Discharge)
Deep Learning Chemical Reaction: Reaction Predictor

Figure 2. Overall reaction prediction framework: (a) A user inputs the reactants and conditions. (b) We identify potential electron donors and acceptors using coarse approximations of electron-filled and -unfilled MOs. (c) Highly sensitive reactive site classifiers are trained and used to filter out the vast majority of unreactive sites, pruning the space of potential reactions. (d) Reactions are enumerated by pairing filled and unfilled MOs. (e) A ranking model is trained and used to order the reactions, where the best ranking one or few represent the major products. The top-ranked product can be recursively chained to a new instance of the framework for multistep reaction prediction.


Deep Learning in Physics: Searching for Exotic Particles
Higgs Boson Detection

Receiver operating characteristics
Area under the curve
Deep network improves AUC by 8%

Collisions at high-energy particle colliders are a traditionally fruitful source of exotic particle discoveries, finding these rare particles requires solving difficult signal-versus-background classification problems, hence machine-learning approaches are often used. Standard approaches have relied on ‘shallow’ machine-learning models that have a limited capacity to learn complex nonlinear functions of the inputs, and rely on a painstaking search through manually constructed nonlinear features. Progress on this problem has slowed, as a variety of techniques have shown equivalent performance. Recent advances in the field of deep learning make it possible to learn more complex functions and better discriminate between signal and background classes. Here, using benchmark data sets, we show that deep-learning methods need no manually constructed inputs and yet improve the classification metric by as much as 8% over the best current approaches. This demonstrates that deep-learning approaches can improve the power of collider searches for exotic particles.
Some Examples
Building Automation

basics: fire, intrusion, climate, energy management
HVAC = Heat, Ventilation and Cooling = air conditioning

visitors, meeting rooms, catering,....
low price tag

Instrumentation & Control Science has become Interdisciplinary
SMART MANUFACTURING

Smart leather is stain repellants and waterproofing agents that protect leather. It is a pH balanced formula that replenishes the essential, natural nutrients that keep natural leather soft and supple. When used on artificial leather surfaces, Smart Leather prevents fading and cracking.

🌟 Builds on the Digital revolution
🌟 Smaller & powerful sensors
🌟 Machine Learning
🌟 Ubiquitous internet
🌟 Artificial Intelligence (AI)
🌟 Labor & Energy Cost
A **cyber-physical system (CPS)** is a system of collaborating computational elements controlling physical entities. CPS are physical and engineered systems whose operations are monitored, coordinated, controlled and integrated by a computing and communication core. They allow us to add capabilities to physical systems by merging computing and communication with physical processes. Physical systems and softwares are interconnected to exchange data through this mechanism. This system involves number of trans-disciplinary subjects such as cybernetics, mechanical engineering, mechatronics design and process science, manufacturing systems, and computer science.
Industry 4.0
Six Design Principles

- **Interoperability**: the ability of *cyber-physical systems* (i.e. work piece carriers, assembly stations and products), humans and Smart Factories to connect and communicate with each other via the *Internet of Things* and the *Internet of Services*

- **Virtualization**: a virtual copy of the Smart Factory which is created by linking sensor data (from monitoring physical processes) with virtual plant models and simulation models

- **Decentralization**: the ability of *cyber-physical systems* within Smart Factories to make decisions on their own

- **Real-Time Capability**: the capability to collect and analyze data and provide the insights immediately

- **Service Orientation**: offering of services (of *cyber-physical systems*, humans and Smart Factories) via the *Internet of Services*

- **Modularity**: flexible adaptation of Smart Factories for changing requirements of individual modules
Top 10 Skills to be relevant in Industry 4.0

**in 2020**

1. Complex Problem Solving
2. Critical Thinking
3. Creativity
4. People Management
5. Coordinating with Others
6. Emotional Intelligence
7. Judgment and Decision Making
8. Service Orientation
9. Negotiation
10. Cognitive Flexibility

**in 2015**

1. Complex Problem Solving
2. Coordinating with Others
3. People Management
4. Critical Thinking
5. Negotiation
6. Quality Control
7. Service Orientation
8. Judgment and Decision Making
9. Active Listening
10. Creativity

Source: Future of Jobs Report, World Economic Forum
CSIR-CENTRAL LEATHER RESEARCH INSTITUTE
AI at CSIR-CLRI

Industry 4.0

- High-Computation Modeling (Chem Lab)
- Surface Imaging using Deep Learning (LPT)
- Smart Leather Chemicals (Chem Lab)
- Industrial Internet of Things (CLAD)
- Cyber Security CISRA
- Additive Mfg 3D Printing/CAD+CAM (Polymer)/SDDC
- Prediction with ANN (Env Tech)
- Process faults & Big data analytics (Chem Eng)
Application of process control in tannery wet operations

Implementation of cleaner production technology is essential for the sustained growth and development of Indian leather industry. Chemical engineering concepts are needed to minimize water usage, toxic chemical load in tannery waste, wastage of chemicals and to increase production capacity. Engineering inputs can give better & safe material handling, process control and provides environmentally cleaner and healthier working atmosphere.

The entire process control operation is designed with following five modules:
- a) Water addition module
- b) Chemical preparation and dosing system
- c) pH control and float recycle system
- d) Drum rotation module
- e) Odor reduction module

The proposed system is an integrated process computer with necessary field instrument and Programmable Logic Controller (PLC) connected in Distributed Control System (DCS) manner.
**Water Addition Module (WAM):** Hot/normal water is added in the drums as per process recipe. Water is also added in load cell tank for dilution of chemicals or is added to batch / bulk chemical tanks for ringing purpose. In case of hot water option, water is heated at 65°C using steam in a heat exchanger. All the sequence of works are controlled by real time software for WAM through PC/PLC. The PC/PLC and field instruments/controllers exchange data between them. Sequences and schedules of operation written using Laddar logic diagram are loaded into PC/PLC memory. The hot water storage tank is linked with the receiving units / equipments by header and branch pipelines as shown below. Based on the requirements of types of water hot/normal, water is added to respective drums through this module and pumps.
Chemical Dosing Module

pH Monitoring

THE LOGIC SHOWN INSIDE DOTTED LINE BOX SHOULD BE DUPLICATED FOR 9 DRUMS WHILE ONE PLC SHOULD HAVE CAPABILITY TO HANDLE ALL DRUMS.
Features of the CADS

Recipe management (download parameters based on selected recipe)
Monitor & Control of the process status
Monitor & report operator’s intervention
Time tagging of all functions
Positioning of the drum in any position
Speed control of the drum via variable frequency drives
Control & Monitoring of the barrier & float & float temperature
All color coded multiple level alarm functionality along with time tagging
Interacts with Chemical feed and Water feed system
Control with both manual & auto modes of all the drum operations
Operate each drum independently & effectively
Initiate each drum with any tanning operation
De-initiate any of the initiated drum at any stage of the operation
Option to extend any of the operation
Wash the mixing tank, storage tanks independently
Data logging and printing
Digital indication of all process variables

Additional Features of the CADS / PLC system are

Alarm : Audio-visual indications for the convenience of the operator
Overall-Drum Status: Can be viewed on the custom graphic screens on the MMI
Hard copies of the detail can be obtained
Mimic panel board: to operate motors (MCB), pumps switches and AC/DC drives
Odor Reduction

Sources & Effects
- NH3, H2S, VOC, gases from degradation of putrescible materials in hides / skins
- These gases must be removed in order to maintain occupational safety, cleaner technology.

VOC – 50 ppm
NH3 – 30 ppm
H2S - 20 ppm

Different **methods of removal** of NH3 and H2S
a) Addition of Chemical Reagents
b) Passing Compressed Air
c) Ozone Oxidation
d) Passing air in counter current to liquor in a packed (activated carbon) bed
e) Biochemical and Biological methods
Odor Abatement BY Bio-Filter

Odor loading less than 1000 ppm
Removal efficiency 94%
Room size: 60 ft X 35 ft X 16 ft high.
Process: 2 Tanning Drums + 4 Paddles
Exhaust fan / Hoods
Microbial Feeding spray and pumps
Recirculation pump
Continuous monitoring of odor gases / Olfactometer or Nasal ranger

Implemented in M/s SA Abdul Azeez Tannery, Erode, TamilNadu

R&D work at CLRI

Automatic Dosing: Process Control

- Water/Chemical weighing & Printing
- Supervisory-Station
- Chemical Dosing
- Drum RPM / Direction
- PH-Check
- Chemical dosing
SCHEME

Rotating Drum Prototype
Transmitter Module
Receiver Module
Monitor Display

AI based measurement of process variables
• **Achievement:** Indian Footwear, Leather & Accessories Development Programme (IFLADP), a special package for employment generation in leather and footwear sector has been launched in December 2017. The package involves implementation of Central Sector Scheme with an approved expenditure of INR 2600 Crore over the three financial years (i.e. 2017-18 to 2019-20)

• Two new branches of FDDI built in Patna and Hyderabad

• INR 1220.32 lakh has been sanctioned under Market Access Initiative scheme for marketing programmes and activities during FY 2017-18.

• 4.44 lakh people trained
Adidas is using robots to produce small-batch, local-market shoes

Shoemaker Adidas just rolled out the first of six local-market running shoes made in its so-called "Speedfactory" in Germany. The running shoe is designed for Londoners, and will be followed by five additional models created for markets like Paris, Los Angeles, and New York. It's an early step in a bold experiment by a global retailer to use time-saving robots to design small-batch collections, a departure from the mass production methods employed by global shoe and apparel brands. Adidas produces about 600 million pairs of shoes other apparel items per year. The brand relies on about a million factory workers in China and Vietnam. But as the shoe industry becomes more focused on hype-driven releases where scarcity and design play an important role in brand credibility, the old global manufacturing chain has become a hinderance. It typically takes Adidas a year or more to design, source, and deliver a shoe to market. Due to the economics of production, the brand must produce minimum batches of 50,000 or 100,000 shoes to make a profit.
next Adidas runners just might be made in America—by a robot. The shoemaker is building what it calls a “Speedfactory” in Atlanta this year. The factory features 74,000 square feet of robotic shoemaking capability. The factory has a capacity of 50,000 pairs of shoes a year.
Adidas analytics technology was designed to understand what motivates consumers and drives decision-making. To facilitate this drive, data scientists at adidas created a Consumer DNA (CDNA) model consisting of re-useable, pre-fabricated analytics components to create a 360 degree Consumer View.

Director of Marketing intelligence (Adidas):
1. What do our digital consumers expect? --Personalization, understand me!
2. What are the key IT success factors enabling change? --Agility, speed, independence and data.
3. Do traditional IT processes and technologies match to the needs of the consumers? --Let’s see

Cost effective Analytic standards
The exports of leather and leather products for April-Jun 2018 have touched USD 1420 million. In order to compete in that global market, Indian leather industry has to gear-up through process automation and other requisites as to comply with industry 4.0 and to become at par with comparable qualities with optimal production as in other countries.

Adidas is using automation to bring manufacturing back to Europe.
CDNA - footwear will be crafted with our individual anatomy and biomechanics as the foundation. The DNA concept leverages rapid manufacturing to create a shoe built not only to your foot contours, but also to how you move. By pairing data acquisition (A sensor shoe tracks your details as you do a test run.), user behavior (Are you running or doing cross-fit?), and rapid prototyping it creates a method of mass-tailoring products. Within hours you have a shoe tailored to your foot, your movement, and your style. Shoes should be built for the way you move.

The first step is to acquire the data that an individual’s shoes will be based on. Each customer’s feet are three dimensionally scanned. Then they put on a pair of special sensor shoes and go for a test run or walk. The sensors track their movement – footfall, pronation, balance, etc. – and combined with the scan and activity type create a usable database to build the new shoes around.

Algorithms are used to translate the data into form and the shoes start to come together. At this point, the customer is able to customize the materials, colors and textures of their shoe. Or they can save a shoe design in advance that can be combined with their foot data when they get to the store. Their design then goes to print, and as they shop the 3d printer creates their shoes.
In the face of potential US tariffs on Chinese-made shoes, numerous world-famous shoe and handbag manufacturers are mulling over shifting sourcing to Vietnam.
Smart leather is stain repellants and waterproofing agents that protect leather. It is a pH balanced formula that replenishes the essential, natural nutrients that keep natural leather soft and supple. When used on artificial leather surfaces, Smart Leather prevents fading and cracking.