A Survey on Applications of Different Artificial Intelligence Computational Techniques for Solving of Engineering Problems

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Abstract

This paper presents the taxonomical review on artificial intelligence computational techniques for solving Engineering problems. The various artificial intelligence computational techniques are presented under along with their background data such as year of invention, author or invented, based on or inspired from what, its application, limitations and future use. The design objective could be simply to minimize the cost of production or to maximize the efficiency of production. Artificial Intelligence computational techniques is a way of making a computer, a computer-controlled robot, or a software think intelligently, in the similar manner the intelligent humans think.SI is an innovative distributed intelligent paradigm for solving optimization problems that originally took its inspiration from the biological examples by swarming, flocking and herding phenomena in vertebrates. There are so many artificial intelligence techniques that can be searched over internet. Here, we have tried to present the most important of them in tabular format along with the other background details. Moreover how much importance they hold in their future. This paper will surely save time for researchers by providing them the details of the immediate artificial intelligence computational techniques in quick format.

Keywords:-Artificial Neural Networks (ANN), Fuzzy Logic (FL), Swarm Intelligence (SI), AlphaGo, Ant Colony Optimisation (ACO), Augmented Transition Network (ATN), Support Vector Machines (SVM), Heuristics, Simple Hierarchical Multi-Perspective (Shrimp), Self-Supervised Tracking (SST), Analytical Approach, Artificial Bee Colony (ABC), Particle Swarm Optimisation (PSO), Expert System Technique (EST), Game Theory (GT), Augmented Transition Network (ATN), Dynamic Time Warping (DTW), Self-Organising Feature Maps (SOM), Machine Theory Of Mind (MT),Analytical Approach, Genetic Algorithm (GA), Evolutionary Programming Techniques (EPT), Hierarchical Task Network (HTN)

Nomenclature

Abbreviations	
SI	Swarm Intelligence
QST	Quantum State Tomography
RF	Random Forest
SVM	Support Vector Machine
ACO	Ant Colony Optimisation

ATN	Augmented Transition Network
HMM	Hidden Markov Models
ANN	Artificial Neural Networks
MDP	Markov Decision Process
GA	Genetic Algorithm
NSM	Nearest Sequence Memory
BN	Bayesian Networks
SATPLAN	Planning as Satisfiability
HTN	Hierarchical Task Network
ABC	Artificial Bee Colony
ML	Machine learning
SGD	Stochastic Gradient Descent
CAD	Computer Aided Designing
SHriMP	Simple Hierarchical Multi-Perspective

1. Introduction

Table 1, column are arranged with the names of techniques along with the corresponding reference numbers such as Dreamcatcher [1], Kdubiq [2], Fuzzy Logic System [3], Expert System Techniques [4], Kalman filtering [5], Swarm Intelligence [6], AUTOMAP [7], QST [8], Alpha Go [9], RF [10], SVM [11], L1 And L2 Regularized Logistic Regression [12], ACO [13], Game Theory [14], Backpropagation [15], Stochastic Gradient Descent (SGD) [16], Hierarchical Representation [17], Actors [18], A * Algorithm [19], Alpha/Beta Pruning [20], ATN [21], SSS* [22], DSSS* [23], Dynamic Time Warping [24], Hill Climbing [25], Pitch Detection Algorithm [26], Self-Organising Feature Maps [27], Earley's Algorithm (Earley Parser) [28], HMM [29], Partial Evaluation Algorithm [30], Relaxation Labelling [31],SHriMP (Simple Hierarchical Multi-Perspective) [32],Heuristics [33], SVMs [34], ANN [35], MDP [36],Natural Language Processing [37],Bio Geography Based Optimization [38],Hebbian Learning [39], Big Data [40], Application Programming Interface (API) [41], Reinforcement Learning [42], Recommender Systems [43], Neuromorphic Computing [44], Computer Vision [45], Mnas Net [46],Google Big query [47], Criq [48], Tensor Flow Object Detection API [49], Machine Theory Of Mind [50],Self-Supervised Tracking Via Video Colorization [51], T-Distributed Stochastic Neighbour Embedding (TSNE) [52],Power Flow(OPF) Based Approach [53],Analytical Approach [54],Gradient Search Method [55],Continuation Power Flow (CPP) [56], Fuzzy C Number (FCN) And Cluster Wise Fuzzy Regression [57], (CWFR) Analysis [58], Genetic Algorithm(GA) [59], Non Dominated Sorting GA II (NSGAII) [60], General Regression Neural Network [61], Plant Growth Simulation Algorithm [62], Body Immune Algorithm [63], Particles Swarm Optimization [64], Modified PSO [65], Discrete PSO [66], Phasor D-PSO [67], Artificial Bee Colony (ABC) [68], Evolutionary Programming Techniques [69], Modified ABC [70], Evolutionary Strategy (EA Techniques) [71], Differential Evolution Techniques [72], Modified Differential Algorithm [73], Pareto Frontier Differential Evolution Algorithm [74], Multi-Cross Learning Based Chaotic Differential Evolution Algorithm [75], Simulated Annealing Approach [76],Tabu Search Approach [77], Parallel Tabu Search Approach [78], Monte Carlo Algorithm [79], Magenta [80], Deep Mind Of Google [81], Cogito [82], Integer Programming Model (Integer Linear Programming) [83], Modified Normal Boundary

Intersection [84], Non-Dominated Sorting GA [85], Generative Topographic Mapping [86], Smith–Waterman Algorithm [87], Needleman–Wunsch Algorithm [88], Cap3 Algorithm [89],Genetic Algorithm(GA) [90],Holonic Manufacturing System [91], FRABIHO [92],DE2MONS [93], Population based Incremental learning [94], HEXQ Algorithm [95], Nested Q-Learning [96],Nearest Sequence Memory [97],Genetic Folding [98],Bayesian Networks [99], SATPLAN (Planning As Satisfiability) [100], PIPSS* [101], Hopfield Network [102], Entropy Notation [103],Graph plan [104],STRIPS (Stanford Research Institute Problem Solver) [105], Hierarchical Task Network [106].

1.1.Motivation of the present work

Literature survey [22], cited in the present work, are pertaining to ATN which is a type of graph theoretic structure used in the operational definition of formal languages, used especially in parsing relatively complex natural languages. Literature review reveals that the there are many applications of the ATN or ATN which include the open source programs. There is a limitation also of the ATN which is that this technique has a heavy dependence on the syntax. In this paper there are many such other artificial intelligence techniques and their applications and limitations along with their future uses which include colour image optimization, understanding the behaviour of the human beings, making big projects and many more.

1.2.Contribution of the paper

This paper considers various types of artificial intelligence techniques such as, Fuzzy Logic, SVMs, Heuristics, Artificial Neural Network, MDP and many more. This paper also gives the applications, limitations and future uses of these artificial intelligence techniques. This paper also differentiates between two similar techniques.

1.3. Organization of the paper

The organization of the rest of the paper is as follows: The next *Section 2*, discusses the survey on Artificial Intelligence Techniques. Finally, the conclusions of the present paper and future research scope are presented in *Section 3.*

2. A Survey on Artificial Intelligence Computational Techniques for Solving Different Engineering Problems

Table 1. A Survey on Artificial Intelligence Computational Techniques for Solving Different Engineering Problems

Sl. No.	Artificial Intelligence Computational Techniques	Year	Invented By	Based	Limitations	Applications	Future
1	Dreamcatcher	2018	Autodesk	It is based on CAD.	It provides the user several alternatives for the certain set of conditional alternatives. It does not give form to a product.	3-Ddesigning/ 3-D printing.	With the help AI technologies intelligent machine designing systems can be made.
2	KDubiq	2016	Google	It is a systematic investigation based on knowledge discovery in global environment.	It's progress is largely dependent on advances in machine learning, data mining areas.Technical limitations in memory, CPU power, bandwidth etc.	To create a unifying framework for examining the mutual dependencies of certain unrelated technologies used in making next-generation intelligent systems viz. machine learning, sensor networks, Web 2.0, privacy, etc.	In long-term research and applications in a new future-oriented discipline ubiquitous knowledge discovery.
3	Fuzzy Logic System	1965	Lotfi Zadeh	Fuzzy set theory	They give same	Recognition of hand-	Online disease diagnostic

					importance to all factors to be combined. In imitation of human thinking process it is not effective.	written symbols. Flight aid for helicopters. Improved fuel consumption for automobile devices.	system. Error correction in information correction.
4	Expert System Techniques	1970	Edward Feigenbaum	Based on LISP programming	Knowledge acquisition problem. System and data base integration were difficult for earlier expert system	Speech Recognition. Pre-term birth risk assessment.	Diagnosing, Assessing, Interpreting, Predicting.
5	Kalman filtering	1960	Rudolf E Kalman	Linear quadratic estimation	Assumptions: State Belief is Gaussian distributed. Both the system and observation models are linear which is not realistic in real life	Attitude and Heading reference systems, Autopilot, Brain-Computer Interface, Radar Tracker	Weather Forecasting, 3-D Modelling, Navigation System, Seismology
6	SI	1989	Gerardo Beni And Jing Wang	Collective behaviour of decentralized, self-organized systems, natural or artificial.	Unpredictable, non-optimal, non-immediate.	Ant based routing, crowd simulation	Human swarming, human tremor analysis
7	AUTOMAP (AUtomatedTransfOrm by Manifold APproximation)	2018	Bo Zhu, Jeremiah Z. Liu , Bruce R. Rosen, Matthew S. Rosen	Image processing technique based on artificial intelligence approach.	In the presence of sensor non-idealities and noise, yhe exact inverse-transform is challenging.	Reducing radiation doses for CT and PET and shortening scan times for MRI.	Image-processing (yields high quality image from less data).
8	QST	1996	Lotfi Zadeh	QST is itself a data-driven problem, in which we aim to obtain a complete quantum-mechanical description of a system, on the basis of a limited set of experimentally accessible measurements.	Experimental quantum computing even in moderate system size is a big challenge to it.	For characterizing optical signals, including measuring the signal gain and loss of optical devices.	In quantum computing and quantum information theory to reliably determine the actual states of the qubits.
9	AlphaGo	1996	Alphabet Inc.'s Google Deep mind	Uses a Monte Carlo tree search algorithm based on machine learning	Go programs based on Monte-carlo tree search algorithm have trouble in facing the Two-safe-group (TSG) test and Seki test.	Used as a program that plays the board game GO.	Alpha Go's approach for a new means of computing potential pharmaceutical drug molecule
10	RF	1995	Tin Kam Ho And Extension by Leo Breiman And Adele Cutler	Based on decision tree learning and tree bagging.	It fails in case of rare outcomes as the algorithm is Bootstrap sampling.	Python implementation with examples in Scikit learning. MATLAB Implementation	It can be used for quality assessments of Wikipedia articles.
11	SVM	1963	Vladimir Vapnik	They are supervised learning models with associated learning algorithms that analyse data used for classification and regression analysis.	Limited Speed and size both in training and testing. Limitation in discrete data.	It is used for detecting spams. It is used for finding a boundary line which separates two classes.	Protein fold and remote homology detection and Bioinformatics.
12	L1 And L2 Regularized Logistic Regression	2000	Lasso Algorithm: Osborne, Presnell, &Turlach	Based on regularization techniques.	In presence of highly correlated features, Lasso does not work good as ridge regression do.	Regression models (Lasso Regression and Ridge Regression).	ML)\training algorithms to reduce model overfitting.
13	ACO	1997	Dorigo And Gambardella	The pheromone-based communication of biological ants is often the predominant paradigm used.	Theoretical analysis is difficult Sequences of random decisions (not independent) Probability distribution changes by iteration Research is experimental rather than theoretical	Routing in telecommunication networks Traveling Salesman Graph Colouring Scheduling	Can be used in dynamic applications (adapts to changes such as new distances, etc)
14	Game Theory	1944	John Von Neumann	It is the study of mathematical models of strategic interaction between rational decision-makers.	Assumptions: 1. The number of players (competitors) in finite. 2. All players act rationally and intelligently.	Used to study a wide variety of human and animal behaviours, applied to political, sociological, and psychological behaviours as well.	According to game theory, it's possible to observe the behaviour of rational players in a game (any two individuals or groups) and predict what decision they'll make next.
15	Backpropagation	1969	Arthur E. Bryson And Yu-Chi-Ho	Basically, a multilayer feed forward network with one layer of hidden units.	Gradient descent with back propagation is not guaranteed to find the	Image pattern recognition, Voice and Speech recognition	Medical diagnosis, Neural Network (NN), Renaissance and de plunging

					global minimum of error function.		
16	SGD	1951	Herbert Robbins and Sutton Monro	Based on gradient descent optimization.	It requires a number of hyperparameters such as the regularization parameter and the number of iterations.	Training a wide range of models in machine learning, including (linear) support vector machines, logistic regression.	Training artificial neural networks; in the Geophysics community applications of Full Waveform Inversion (FWI).
17	Hierarchical Representation	1960s	IBM	Based on database management system.	Due to one-to-many relationships its structure is simple but inflexible.	IBM Information Management System (IMS) and the RDM Mobile.	Storing geographic information and file systems.
18	Actors	1977	Hewitt	The actor model in computer science is a mathematical model of concurrent computation that treats "actors" as the universal primitives of concurrent computation.	Misunderstanding of the actor model caused by all the marketing, may reintroduce the problems that the Actor Model tries to solve.	Message-passing semantics, Direct communication and asynchrony.	It can be used for making big projects using programming language like JAVA.
19	A * Algorithm	1968	Peter Hart, Nils Nilsson And Bertram Raphael	It is a computer algorithm that is widely used in pathfinding and graph traversal, which is the process of finding a path between multiple points, called "nodes"	A* focuses to reach the goal node from the current node, not to reach every other node.	For the common pathfinding problem in applications such as games, but was originally designed as a general graph traversal algorithm.	It enjoys widespread use due to its performance and accuracy.
20	Alpha/Beta Pruning	1958	John McCarthy	The algorithm maintains two values, alpha and beta, which represent the minimum score that the maximizing player is assured of and the maximum score that the minimizing player is assured of respectively	Evaluations of the utility of a node are usually not exact but crude estimates of the value of a position and as a result large errors could be associated with them.	Open source programs that implements the alpha-beta pruning like Stock fish(chess)	Algorithms like SSS* using best-use strategy
21	ATN	1980	W. A. Woods	ATN is a type of graph theoretic structure used in the operational definition of formal languages, used especially in parsing relatively complex natural languages	A limitation to the ATN approach is that the heavy dependence on syntax	Especially, in parsing relatively complex natural languages.	More efficient parsing of the sentences, grammatically.
22	SSS*	1979	George Stockman	Based on the notion of solution trees	It has large memory requirements that make the algorithm impractical for realapplications.	An action function that, given a state and an action, returns a new state.	For searching minimax trees and game trees.
23	DSSS*	1942	Gustav Guanella	Basically, it is a spread spectrum modulation technique.	It needs a wideband channel with small phase distortion, having large acquisition time it gets slow.	Used for low probability of intercept signal, military and many commercial applications.	Various uses like-Radio-controlled model Automotive vehicles.
24	Dynamic Time Warping	1978	Sakoe,H. and Chiba, S	Time series alignment algorithm.	It needs actual training examples, limited number of templates.	Spoken-word recognition	Correlation Power Analysis
25	Hill Climbing	1983	Xi, B., Liu, Z., Raghavachari, M., Xia, C. H., & Zhang, L.	It is a variant(type) of generate and test algorithm, based on Heuristic search.	Being a local method, it considers only immediate consequences of choice to make decisions, global information might be encoded in heuristic functions.	Basically, used for mathematical optimization problems.	Various uses like-Radio-controlled model Automotive vehicles.
26	Pitch Detection Algorithm	1969	B. Gold and L. R. Rabiner	Based on time-frequency analysis.	It does not work well with complicated waveforms which are composed of multiple sine waves with differing periods or noisy data.	In estimation of the pitch or fundamental frequency of a quasiperiodic or oscillating signal.	Phonetics, music information retrieval, speech coding.
27	Self-Organising Feature Maps	Early 1980s	Professor TeuvoKohonen	Based on time-frequency analysis.	It needs a wideband channel with small phase distortion, having large acquisition time it gets	An action function that, given a state and an action, returns a new state.	Seismic facies, Failure Mode and Effect Analysis.

					slow.		
28	Earley's Algorithm (Earley Parser)	1968	Jay Earley	Based on dynamic programming	It may suffer problems with certain nullable grammars.	For parsing strings that belong to a given context free language.	For parsing in computational linguistics.
29	HMM	1960	Ruslan L. Stratonovich	Based on Markov Process and can be represented as the simplest dynamic Bayesian network.	They operate using discrete states and they take into account only the last known state.	Single-molecule kinetic analysis, Speech recognition, including Siri Speech synthesis Part-of-speech tagging, Document separation in scanning solutions	Computational finance,Cryptanalysis, Gene prediction.
30	Partial Evaluation Algorithm	1970s	Yoshihiko Futamura (Fatamura Projections)	The theoretical foundation for it is Kleene's S-M-N theorem from recursive function theory.	If the information in a program is available only dynamically (i.e., at run time) then data structures cannot be propagated throughout the code.	Futamura projections	Different types of program optimization by specialization.
31	Relaxation Labelling	1985	Kittler, J., & Illingworth, J.	Based on Markov Process and can be represented as the simplest dynamic Bayesian network.	Relaxation strategies do not necessarily guarantee convergence	In estimation of the pitch or fundamental frequency of a quasiperiodic or oscillating signal.	Phonetics, music information retrieval, speech coding.
32	SHriMP	2015	Developed with Support from The Natural Sciences and Engineering Research Council of Canada (NSERC), Defence Research and Development Canada (DRDC), And IBM Centres for Advanced Studies - Toronto.	The theoretical foundation for it is Kleene's S-M-N theorem from recursive function theory.	They operate using discrete states and they take into account only the last known state.	For parsing strings that belong to a given context free language.	For parsing in computational linguistics.
33	Heuristics	1970s and 80	Herbert A. Simon	It is an approach to solving problems which includes a practical method which is not perfect but sufficient enough to reach a particular goal	It requires multiple experts. It may identify more minor issues and fewer major issues during evaluation.	It is used to find a practical way of solving problems. It is basically simulation without algorithm.	Computational finance,Cryptanalysis, Gene prediction.
34	SVMs	1963	Vladimir Vapnik	They are supervised learning models with associated learning algorithms that analyse data used for classification and regression analysis.	Limited Speed and size both in training and testing. Limitation in discrete data.	It is used for detecting spams. It is used for finding a boundary line which separates two classes.	Evolution into long term potentiation models.
35	ANN	1958	Frank Rosenblatt	ANN can be described as processing devices that are loosely modelled after the neural structure of a brain.	Hardware dependence and unexplained behaviour of the network. Difficulty of showing the problem to the network	For image recognition purposes. For speech recognition purposes.	Language translators. Semantic Folding.
36	MDP	1950	Markov	It provides a mathematical framework for modelling decision making in situations where outcomes are partly random and partly under the control of a decision maker.	Curse of dimensionality. Exponential growth in state space.	Robotics. Automatic control.	Economics and manufacturing
37	Natural Language Processing	1969	Roger Schank	It is used to refer to everything from speech recognition to language generation, each requiring different techniques	Dependency on High computing power. Conventional vector-based approaches are not fine-grained enough to be precise.	Part-of-Speech tagging, Named Entity Recognition, and Parsing.	Language translators. Semantic Folding.
38	Bio Geography Based Optimization	2008	Dan Simon	Belongs to the class of meta heuristics.	Poor in exploiting the solutions, no provision for selecting the best members from each generation	Used to optimize multi-dimensional real valued functions.	Colour image quantization. Feature selection in DNA micro array data that is used for cancer classification.
39	Hebbian Learning	1940s	D.O. Hebb	Based on mechanism of neural plasticity.	Correlation based synaptic plasticity are typically unstable.	Computational models of Turing's B type machine.	Evolution into long term potentiation models.
40	Big Data	2007	Google	It is an approach to solving problems which includes a	Hardware dependence and unexplained	Tesla's fleet learning,	For parsing in computational linguistics.

				practical method which is not perfect but sufficient enough to reach a particular goal	behaviour of the network. Difficulty of showing the problem to the network		
41	Application Programming Interface (API)	2009	Chen, Mingtse, Anil K. Annadata, and Leon Chan	It provides a mathematical framework for modelling decision making in situations where outcomes are partly random and partly under the control of a decision maker.	Curse of dimensionality. Exponential growth in state space.	Robotics. Automatic control.	Economics and manufacturing
42	Reinforcement Learning	1998	Sutton, Richard S., Andrew G. Barto, and Francis Bach	It is based on machine learning.	Memory expensive, very difficult to completely determine the current state	Used in robotics for industrial automation, in machine learning and data processing, to create training systems that provide custom instruction.	Learning the way human being learns e.g., AlphaGo.
43	Recommender Systems	1987	Resnick, Paul, and Hal R. Varian	It considers users past preferences e.g. YouTube recommendations	Limited Speed and size both in training and testing. Limitation in discrete data.	Part-of-Speech tagging, Named Entity Recognition, and Parsing.	Computational finance,Cryptanalysis, Gene prediction.
44	Neuromorphic Computing	1990	Mead, Carver	Based on Markov Process and can be represented as the simplest dynamic Bayesian network.	Relaxation strategies do not necessarily guarantee convergence	Used to optimize multi-dimensional real valued functions.	For parsing in computational linguistics.
45	Computer Vision	2003	Hartley, Richard, and Andrew Zisserman	Similar to human vision	It requires multiple experts. It may identify more minor issues and fewer major issues during evaluation.	In estimation of the pitch or fundamental frequency of a quasiperiodic or oscillating signal.	Computational finance,Cryptanalysis, Gene prediction.
46	MnasNet	2008	Tan, Mingxing	Based on mechanism of neural plasticity.	Poor in exploiting the solutions, no provision for selecting the best members from each generation	It is used for detecting spams. It is used for finding a boundary line which separates two classes.	Evolution into long term potentiation models.
47	Google Big query	2011	Google	Enables interactive analysis of massively large datasets working in conjunction with Google Storage.	It limits the maximum rate of incoming request and enforces appropriate quotas on a per-project basis.	Storing and querying massive data sets.	Can run the 'canonical analytics query'.
48	CRIQ	2018	Alan Ho&Dave Bacon	Based on time-frequency analysis.	It does not work well with complicated waveforms which are composed of multiple sine waves with differing periods or noisy data.	In estimation of the pitch or fundamental frequency of a quasiperiodic or oscillating signal.	Phonetics, music information retrieval, speech coding.
49	TensorFlow Object Detection Api	2015	Google Brain Team	An open-source software library for dataflow programming across a range of tasks.	Missing symbolic loops. No support for windows, computation speed.	Real time object detection	Computational finance,Cryptanalysis, Gene prediction.
50	Machine Theory of Mind	2018	Neil Rabinowitz, Frank Perbet, Francis Song, Chiuan Zhang, S M Ali Eslami, Mathew Potpinick	Based on TOMNET (theory of mind neural network)	Limited Speed and size both in training and testing. Limitation in discrete data.	It is used to build a system that learns how to model other agents	Computational finance,Cryptanalysis, Gene prediction.
51	Self-Supervised Tracking Via Video Colorization	2018	Wiles, Olivia, A. Koepke, and Andrew Zisserman	Method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution.	It copies colour from a single reference frame.	Activity recognition. Object Interaction. Video stylization.	To track objects in videos without supervision.
52	T-Distributed Stochastic Neighbour Embedding (TSNE)	2008	Maaten, L. V. D., & Hinton, G	It is based on machine learning.	It provides the user several alternatives for the certain set of conditional alternatives. It does not give form to a product.	To interpret deep neural network outputs in tools such as the TensorFlow Embedding Projector and tensor board	To track objects in videos without supervision.
53	Power Flow (OPF) Based Approach	1985	Sun, D. I., Ashley, B., Brewer, B., Hughes, A., &Tinney, W. F	Basically, it is a spread spectrum modulation technique.	It needs a wideband channel with small phase distortion, having large acquisition time it gets	Used for low probability of intercept signal, military and many commercial applications.	Various uses like-Radio-controlled model Automotive vehicles.

					slow.		
54	Analytical Approach	384 to 322 BC	Aristotle	A peer-reviewed scientific journal publishing original (primary) research covering the development of analytical techniques.	Limited Speed and size both in training and testing. Limitation in discrete data.	It is used for detecting spams. It is used for finding a boundary line which separates two classes.	Phonetics, music information retrieval, speech coding.
55	Gradient Search Method	1995	A Cauchy	Based on time-frequency analysis.	It does not work well with complicated waveforms which are composed of multiple sine waves with differing periods or noisy data.	In estimation of the pitch or fundamental frequency of a quasiperiodic or oscillating signal.	Phonetics, music information retrieval, speech coding.
56	Continuation Power Flow (CPP)	1996	P.R Bijwe and R.S Tare(P)	Based on time-frequency analysis.	Powerful hardware must be used	Used to obtain P-V curve of power system, Voltage stability assessment.	Divergence due to ill conditioning is not encountered at the critical point even when single precision computation is used.
57	Fuzzy C Number (FCN) And Cluster Wise Fuzzy Regression	1973	J.C Dunn	Based on k-means algorithm	It may fail to detect clusters of different sizes	To analyse gene expression data	Image processing
58	(CWFR) Analysis	1998	Yang, Miin-Shen, and Cheng-Hsiu Ko	Basically, it is a spread spectrum modulation technique.	It needs a wideband channel with small phase distortion, having large acquisition time it gets slow.	Used for low probability of intercept signal, military and many commercial applications.	Various uses like-Radio-controlled model Automotive vehicles.
59	GA	1970s	John Holland	Method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution.	Gas tend to converge towards local optima or even arbitrary points rather than the global optimum of the problem. This means that it does not "know how" to sacrifice short-term fitness to gain longer-term fitness.	Time tabling and scheduling problems	Problem domains that have a complex fitness landscape as mixing
60	Non-Dominated Sorting Ga II (NSGAII)	1995	Srinivas And Dev	Multiple objective optimization	It provides the user several alternatives for the certain set of conditional alternatives. It does not give form to a product.	Pareto solutions efficiently	Image processing
61	General Regression Neural Network	1991	D.F Specht	Based on non-parametric regression.	No optimal method to improve it	Regression prediction classification	Can also be a good solution for online dynamical system
62	Plant Growth Simulation Algorithm	1968	Aristid Lindenmayer	Plant morphology with computer software	Powerful hardware must be used	Usually used to simulate growth of e-trees	Field of complexity science and A-life
63	Body Immune Algorithm	1986	Farmer, Packard And Perelson	Rule based machine learning system	DNA computing is not under this	Computational problems from mathematics, engineering and information technology	Biologically inspired computing
64	Particles Swarm Optimization	1995	Kennedy J., Eberhart	Based on stochastic optimization technique	Low convergence rate in the iterative process	Simulation of social behaviour, evolving neural networks	To maintain a population of particles
65	Modified PSO	1997-98	Eberhart And Schi	Based on simulated annealing algorithm	Limited Speed and size both in training and testing. Limitation in discrete data.	Optimum design of PID controller	Various uses like-Radio-controlled model Automotive vehicles.
66	Discrete PSO	1997	Kennedy J., Eberhart	Particle swarm optimization technique	Curse of dimensionality. Exponential growth in state space.	It is used for detecting spams. It is used for finding a boundary line which separates two classes.	Future paths for integer programming
67	Phasor D PSO	2012	Bae, In-Su, and Jin-O. Kim	Based on time-frequency analysis.	It needs a wideband channel with small phase distortion, having large acquisition time it gets slow.	To analyse gene expression data	Various uses like-Radio-controlled model Automotive vehicles.
68	ABC	2005	Karaboga	Based on intelligent foraging behaviour of	It may suffer problems with certain nullable	Understanding the behaviour of honey	Ecologically successful

				honey bee swarm	grammars.	bees towards nectar	
69	Evolutionary Programming Techniques	1960	Lawrence J. Fogel	Genetic programming	Structure of programs optimized is fixed	Space craft antenna, air foil design	Increase in the performance of computer
70	Modified ABC	2003	Kanno, Akira	Based on k-means algorithm	It may fail to detect clusters of different sizes	To analyse gene expression data	Image processing
71	Evolutionary Strategy (EA Techniques)	1960	Lawrence J. Fogel	Subset of Evolutionary programming techniques	Structure of programs optimized is fixed	Space Craft Antenna, Air foil design	Increase in the performance of computer
72	Differential Evolution Techniques	1996	Storn	Based on metaheuristics	Gas tend to converge towards local optima or even arbitrary points rather than the global optimum of the problem. This means that it does not "know how" to sacrifice short-term fitness to gain longer-term fitness.	Varying optimization problems	Synchronization with Qazi-Newton methods
73	Modified Differential Algorithm	2016	Qiao, D.P, Pang	Based on metaheuristics	No optimal method to improve it	Varying optimization problems	Synchronization with Qazi-Newton methods
74	Pareto Frontier Differential Evolution Algorithm	1999	C. S. Chang, D. Y. Xu, And H. B. Quek	Differential evolution algorithm for multi objective optimization	It may fail to detect clusters of different sizes	Activity recognition. Object Interaction. Video stylization.	Ecologically successful
75	Multi-Cross Learning Based Chaotic Differential Evolution Algorithm	1997	Storm and Price	Based on metaheuristics and evolutionary programming techniques	Curse of dimensionality. Exponential growth in state space.	Varying optimization problems	Synchronization with Qazi-Newton methods
76	Simulated Annealing Approach	1979	Khachaturyn, Semenovskaya	Based on metallurgical annealing	Low convergence rate in the iterative process	Often used when search space is discrete	Thermodynamic systems
77	Tabu Search Approach	1986	Fred W. Glover	Similarity coefficient for cell formation	DNA computing is not under this	Local search method used for mathematical optimization	Future paths for integer programming
78	Parallel Tabu Search Approach	1993	Crainic, Toulouse, And Gendreau	Based on 3-D classification of algorithmic features	It may fail to detect clusters of different sizes	For solving container loading problems	Faster versions of sequential TS implementations, distributed parallel approach in TS
79	Monte Carlo Algorithm	1947	Nicholas Metropolis	Resource restricted algorithm providing answers based on probability.	It is not an exact algorithm, actually it is a heuristic one using randomness.	Solovay-Strassen primality test, the Baillie-PSW primality test, the Miller-Rabin primality test	Schreier-Sims algorithms in computational group theory
80	Magenta	2015	Google	Based on metaheuristics	Gas tend to converge towards local optima or even arbitrary points rather than the global optimum of the problem. This means that it does not "know how" to sacrifice short-term fitness to gain longer-term fitness.	Varying optimization problems	Synchronization with Qazi-Newton methods
81	Deep Mind of Google	2010	Demis Hassabis, Shane Legg And Mustafa Suleyman	Based on neural network that learns how to play video games as of humans	Gradient descent with back propagation is not guaranteed to find the global minimum of error function.	Deep reinforcement learning, alpha go	Wavenat, Google's mobile operating systems
82	Cogito	2007	Petr Baudis	Based on metaheuristics	Gas tend to converge towards local optima or even arbitrary points rather than the global optimum of the problem. This means that it does not "know how" to sacrifice short-term fitness to gain longer-term fitness.	Varying optimization problems	Synchronization with Qazi-Newton methods
83	Integer Programming Model (Integer Linear Programming)	1983	H.W. Lenstra[P]	Mathematical optimization	It is not feasible for the ILP to round off the relaxation solution.	Production planning, scheduling	Telecommunication networks, cellular networks
84	Modified Normal Boundary Intersection	1998	I. Das And J.E. Dennis	A scalarization scheme with a uniform spread in parameters will give rise to a	It is fairly demanding of time.	To find pareto optimal solutions for general nonlinear multi-objective optimization	Future paths for integer programming

				near uniform spread in points on the efficient frontier.		problem.	
85	Non-Dominated Sorting GA	1994	N Srinivas and K, Deb	Multiple Objective Optimization (MOO) algorithm	Time complexity, the lack of elitism	Water Distribution networks	Ruby Programming Language
86	Generative Topographic Mapping	1996	Christopher Bishop	Based on machine learning	Curse of dimensionality. Exponential growth in state space.	To form a nonlinear latent variable model	Deformational modelling
87	Smith–Waterman Algorithm	1981	T.F. Smith and M.S. Waterman	Based on an earlier model appropriately named Needleman and Wunsch	It is fairly demanding of time.	SIMD technology available in Intel Pentium MMX processors, gpus.	Determining similar regions between two strings of nucleic acid sequences or protein sequences.
88	Needleman–Wunsch Algorithm	1970	Saul B. Needleman And Christian D. Wunsch	Based on Dynamic programming.	Negative scoring matrix cells are set to zero, which renders the (thus positively scoring) local alignments visible	Used in bioinformatics to align protein or nucleotide sequences.	In field of Computer stereo vision (stereo matching).
89	Cap3 Algorithm	2001	Google	Based on stochastic optimization technique	Low convergence rate in the iterative process	Simulation of social behaviour, evolving neural networks	To maintain a population of particles
90	GA	1970s	John Holland	Method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution.	Gas tend to converge towards local optima or even arbitrary points rather than the global optimum of the problem. This means that it does not "know how" to sacrifice short-term fitness to gain longer-term fitness.	Time tabling and scheduling problems	Problem domains that have a complex fitness landscape as mixing
91	Holonic Manufacturing System	1997	Valckenaers, P. A. U. L.	Basically, a multilayer feed forward network with one layer of hidden units.	Gradient descent with back propagation is not guaranteed to find the global minimum of error function.	Image pattern recognition, Voice and Speech recognition	Medical diagnosis, Neural Network (NN), Renaissance and de plunging
92	Frabiho	2005	Marcos, M	They are supervised learning models with associated learning algorithms that analyse data used for classification and regression analysis.	Limited Speed and size both in training and testing. Limitation in discrete data.	It is used for detecting spams. It is used for finding a boundary line which separates two classes.	Evolution into long term potentiation models.
93	De2mons	2009	Plemenos, Dimitri, and George Miaoulis	Based on 3-D classification of algorithmic features	It may fail to detect clusters of different sizes	For solving container loading problems	Faster versions of sequential TS implementations, distributed parallel approach in TS
94	Population based Incremental learning	1994	Shumeet Baluja	Based on GAs.	Negative scoring matrix cells are set to zero, which renders the (thus positively scoring) local alignments visible	Combinatorial optimisation problems.	Ruby Programming Language
95	Hexq Algorithm	1994	Bernhard Hengst	Resource restricted algorithm providing answers based on probability.	It is not an exact algorithm, actually it is a heuristic one using randomness.	Solovay-Strassen primality test, the Baillie-PSW primality test, the Miller-Rabin primality test	Schreier-Sims algorithms in computational group theory
96	Nested Q-Learning	1965	Bruce L. Digney	Based on metaheuristics	Gas tend to converge towards local optima or even arbitrary points rather than the global optimum of the problem. This means that it does not "know how" to sacrifice short-term fitness to gain longer-term fitness.	Varying optimization problems	Synchronization with Qazi-Newton methods
97	NSM	1995	Meyers, Ray J., Timothy J. Tautges, and Philip M. Tuchinsky	Based on Dynamic programming.	Negative scoring matrix cells are set to zero, which renders the (thus positively scoring) local alignments visible	Used in bioinformatics to align protein or nucleotide sequences.	In field of Computer stereo vision (stereo matching).

98	Genetic Folding	2010	Mohammad Mezher And Maysam F Abbod	Novel chromosomes organisation	Gradient descent with back propagation is not guaranteed to find the global minimum of error function.	For solving container loading problems	Ruby Programming Language
99	BN	2005	Google	Based on dynamic programming	It may suffer problems with certain nullable grammars.	For parsing strings that belong to a given context free language.	For parsing in computational linguistics.
100	SATPLAN	1992	H. A. Kautz And B. Selman	Automated planning	It may suffer problems with certain nullable grammars.	It converts the planning problem instance into an instance of the Boolean satisfiability problem	Deformational modelling
101	PIPSS*	2008	Plaza, J	Basically, a multilayer feed forward network with one layer of hidden units.	Gradient descent with back propagation is not guaranteed to find the global minimum of error function.	Image pattern recognition, Voice and Speech recognition	Medical diagnosis, Neural Network (NN), Renaissance and de plunging
102	Hopfield Network	1982	John Hopfield	Recurrent artificial neural network	It may fail to detect clusters of different sizes	For image detection and recognition, enhancement of x-ray images, medical image restoration, speech & pattern recognition	Faster versions of sequential TS implementations, distributed parallel approach in TS
103	Entropy Notation	1992	Uspensky, Vladimir A	Resource restricted algorithm providing answers based on probability.	It is not an exact algorithm, actually it is a heuristic one using randomness.	Solovay-Strassen primality test, the Baillie-PSW primality test, the Miller-Rabin primality test	Schreier-Sims algorithms in computational group theory
104	Graph plan	1995	Avrim Blum And Merrick Furst	They are supervised learning models with associated learning algorithms that analyse data used for classification and regression analysis.	Limited Speed and size both in training and testing. Limitation in discrete data.	It is used for detecting spams. It is used for finding a boundary line which separates two classes.	Evolution into long term potentiation models.
105	STRIPS (Stanford Researc h Institute Problem Solver)	1971	Richard Fikes And Nils Nilsson	Multiple Objective Optimization (MOO) algorithm	Time complexity, the lack of elitism	Water Distribution networks	Ruby Programming Language
106	HTN	1994	Erol, Kutluhan, James A. Hendler, and Dana S. Nau	Based on dynamic programming	It may suffer problems with certain nullable grammars.	For parsing strings that belong to a given context free language.	For parsing in computational linguistics.

3. Conclusions and Future Scope of Research Work

3.1 Conclusions

This paper presents the survey on different artificial intelligence computational techniques for solving engineering problems such as capacitor, distributed generations, FACTS controllers planning. This paper discusses more than a hundred artificial techniques including their applications, limitations and future use. The motive of this research paper was to give readers an idea about the development and the future use of artificial intelligence techniques.

3.2 Recommendations for scope of future research work

The following recommendations for the scope of research work in this direction may be carried out in future.

- Application of Artificial Intelligence (AI) techniques for optimal location and properly coordinated control of DGs and FACTS controllers such as Static Compensator (STATCOM) and Distributed-STATCOM (D-STATCOM) in DNs with static load models only for better DN performance indices.
- Application of AI techniques for optimal location and properly coordinated control of DGs and FACTS controllers such as STATCOM and D-STATCOM in DNs with static as well as realistic load models for better DN performance indices.

- Application of hybrid AI techniques for optimal location and properly coordinated control of DGs and FACTS controllers such as STATCOM and D-STATCOM in DNs with static load models only for better DN performance indices.
- Application of hybrid AI techniques for optimal location and properly coordinated control of DGs and FACTS controllers such as STATCOM and D-STATCOM in DNs with static as well as realistic load models for better DN performance indices.
- Application of AI techniques for optimal location and properly coordinated control of DGs and FACTS controllers such as STATCOM and D-STATCOM in DNs with static load models with seasonal criterion only for better DN performance indices.
- Application of AI techniques for optimal location and properly coordinated control of DGs and FACTS controllers such as STATCOM and D-STATCOM in DNs with static load models with seasonal criterion as well as realistic load models for better DN performance indices.
- Application of hybrid AI techniques for optimal location and properly coordinated control of DGs and FACTS controllers such as STATCOM and D-STATCOM in DNs with static load models with seasonal criterion only for better DN performance indices.
- Application of hybrid AI techniques for optimal location and properly coordinated control of DGs and FACTS controllers such as STATCOM and D-STATCOM in DNs with static load models with seasonal criterion as well as realistic load models for better DN performance indices.

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Bibliography

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