

Power Distribution System Planning: Different Models and Solution Strategies

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Overview

- ❑ Introduction
- ❑ Classification of the existing approaches
- ❑ Discussion on different planning models
- ❑ Discussion on different solution strategies
- ❑ Results of a typical planning approach
- ❑ Recent trends

What is Distribution System Planning?

To determine a network that:

- ❖ is capable of supplying all demand nodes economically by maintaining capacity constraints of substations and feeders.
- ❖ contributes low power loss.
- ❖ can maintain desired voltage profile at all nodes.
- ❖ is capable of supplying future load demand.

Distribution system planning variables

- Location and size of new substations
- Number of feeders and their routes
- Conductor sizes of feeder branches
- Conductor replacement of existing feeder branches (if required)
- Number and locations of sectionalizing switches
- Number and locations of tie-lines

Optimization objectives and constraints:

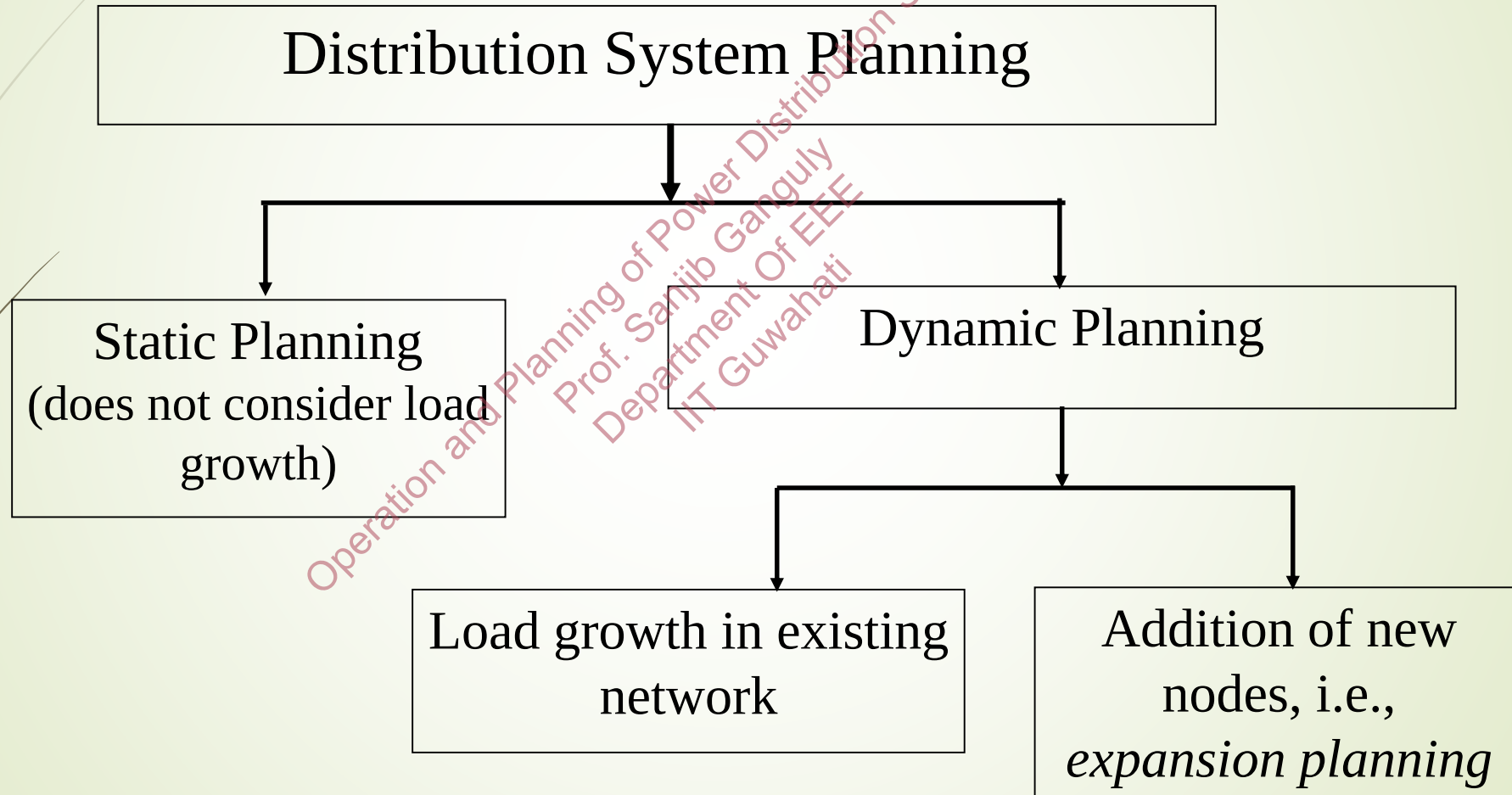
Objectives:

- Minimization of total installation cost of new substations/feeder branches
- Minimization of power loss
- Minimization of supply interruptions

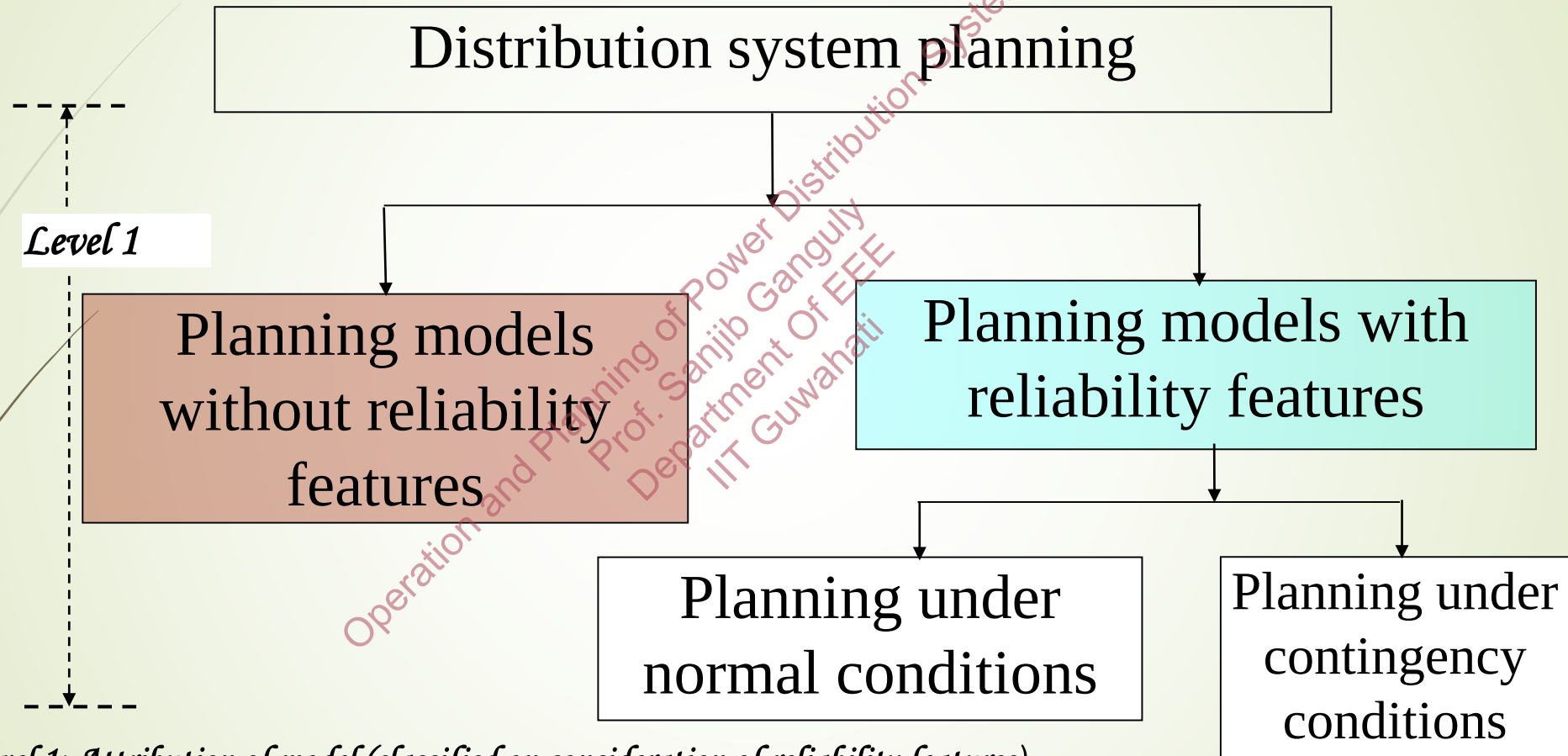
Constraints:

- Power balance
- Substation capacity
- Feeder branch capacity
- Node voltage deviation

A broad classification of distribution system planning



Classification of distribution system planning schemes

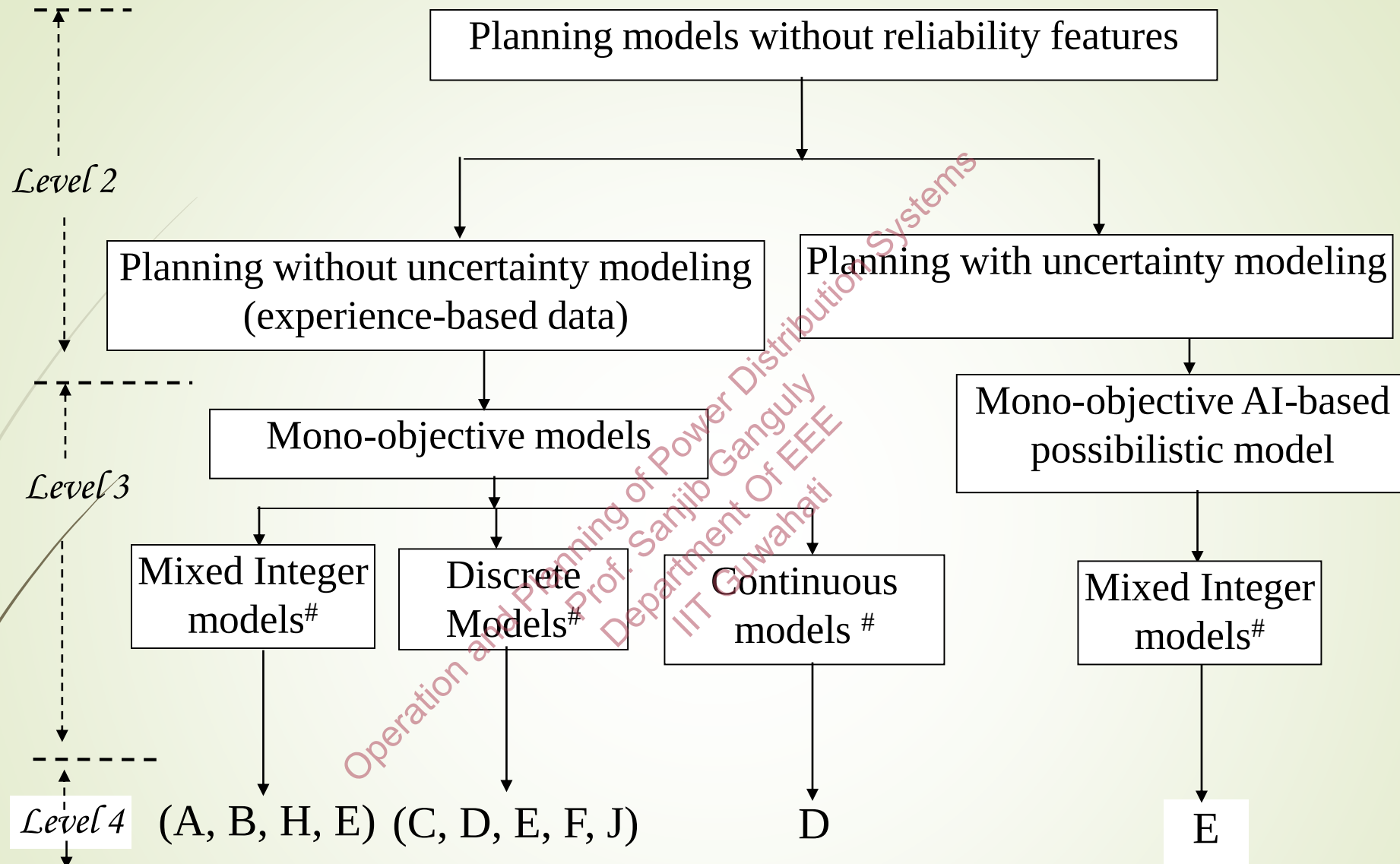


Level 1: Attribution of model (classified on consideration of reliability features)

Level 2: Classification based on uncertain data modeling

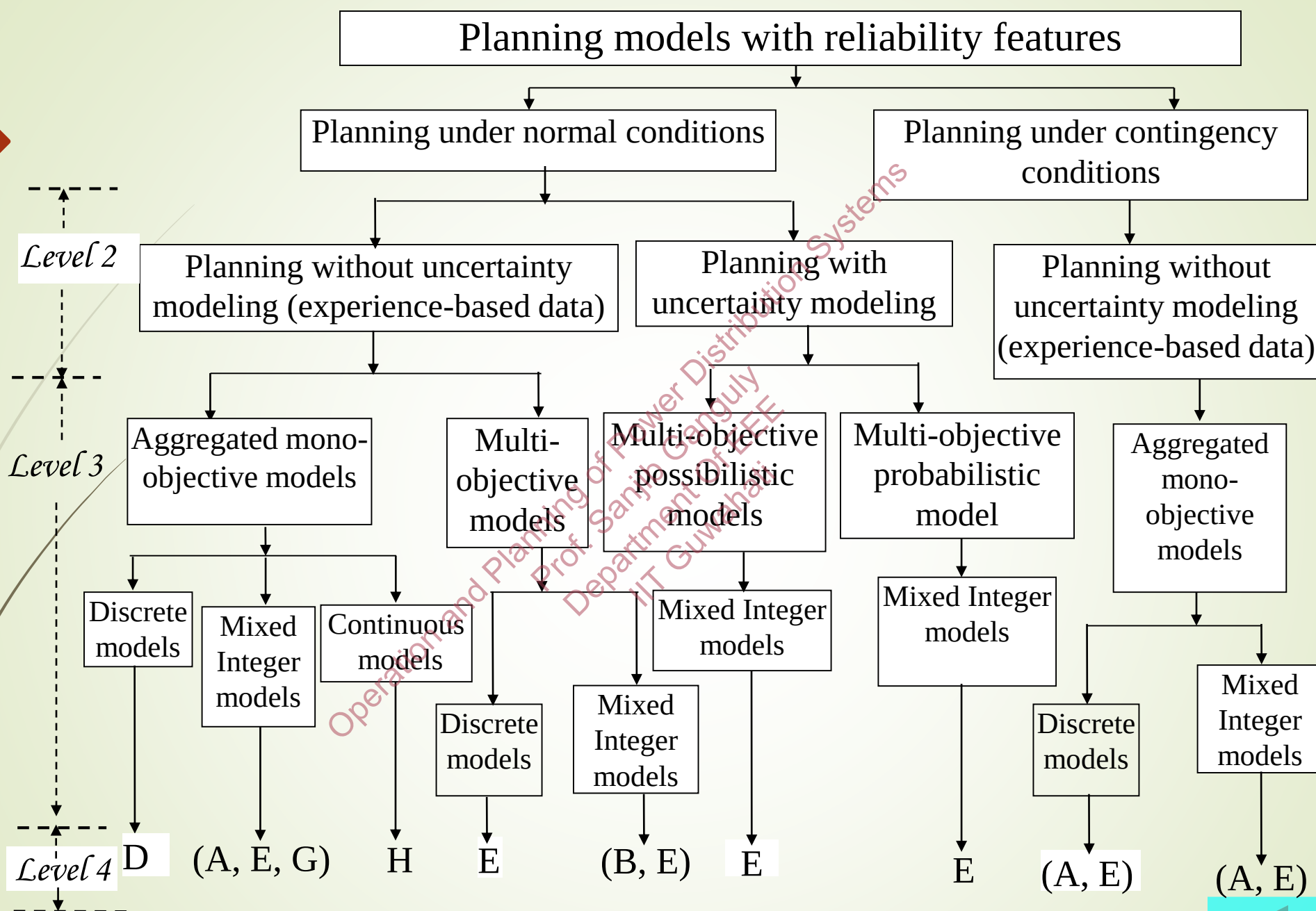
Level 3: Type of problem formulation (based on planning decision variables, objective function)

Level 4: Different solution strategies



A=Linear and Integer Programming, B= Branch and bound, Bender's decomposition, C=Branch Exchange, D=Dynamic Programming, E= Artificial Intelligence techniques, F=ANN, G=Network flow programming, H=Nonlinear programming, I=Multiple tasks based algorithm





Classification of solution strategies

Deterministic algorithms

- Mixed integer programming
- Branch and bound
- Bender's decomposition
- Dynamic programming

Meta-heuristics-based algorithms

- Expert system
- Branch exchange
- Network flow programming
- Simulated annealing
- population-based algorithms
 - Genetic algorithm
 - Ant colony optimization
 - Artificial immune system
 - Particle swarm optimization

Summary of solution strategies

- ❖ In most of the multi-objective planning the evolutionary algorithms are used as:
 - Multi-point search helps to obtain a set of Pareto-approximation solutions in a single run.
 - They can handle nonlinear, non-convex, non-differentiable problems effectively.
 - They do not suffer from the curse of dimensionality.
- ❖ A drawback of evolutionary algorithms is that the convergence is not always guaranteed.

A Mono- and multi-objective planning of electrical distribution systems using particle swarm optimization (PSO)

Objectives:

- ❑ To investigate the applicability of particle swarm optimization (PSO) for mono- and multi-objective planning of electrical distribution systems
- ❑ To show the performance of the PSO-based planning algorithm for both static and expansion planning using large-scale test systems
- ❑ To provide performance assessment of different PSO variants using statistical tests

Objective functions

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(i) Total installation and operational cost

$$C_{IO} = \sum_{(i,j) \in A_{br}} \left\{ (C_{i,j}^{I_b} l_{i,j}) + (C_{i,j}^{M_b} l_{i,j}) t_a + C^V P_{i,j}^l t_a \vartheta D_F \right\} y_{i,j} \\ + \sum_{(i,j) \in E_{br}} \left\{ (C_{i,j}^R l_{i,j}) + (C_{i,j}^{M_b} l_{i,j}) t_a + C^V P_{i,j}^l t_a \vartheta D_F \right\} + \sum_{k=1}^{N_s} C_k^{I_s}$$

(ii) Total interruption cost

$$C_{IN} = \sum_{(i,j) \in A_{br}} (C_{i,j}^{Ot} + C_{i,j}^{NDE} d_j + C_{i,j}^{CCDC} d_j) y_{i,j} \lambda_j l_j P_j t_a + \sum_{(i,j) \in E_{br}} (C_{i,j}^{Ot} + C_{i,j}^{NDE} d_j + C_{i,j}^{CCDC} d_j) \lambda_j l_j P_j t_a$$

$C_{i,j}^{I_b} (C^R)$	branch installation (conductor replacement) cost per unit length (\$ / km)
$C_{i,j}^{M_b} (C^V)$	annual branch maintenance cost per unit length (cost of energy losses in \$ / year)
$l_{i,j} (P_{i,j})$	length (power flow in MW) of branch in between nodes i, j (km)
$y_{i,j}, y_k$	binary variable = 1 if selected, otherwise = 0
$A_{br} (E_{br})$	total number of allowable (existing) branches for feeder routes
$P_{i,j}^l (\vartheta)$	power loss in branch ij (load loss factor)
$t_a (D_F)$	total planning time (discount factor)
$C_k^{I_s} (N_s)$	substation installation cost (number of substations)
$\lambda(d)$	average branch failure rate in failure / km / year (failure duration in hr / failure / year)

Test systems/networks used

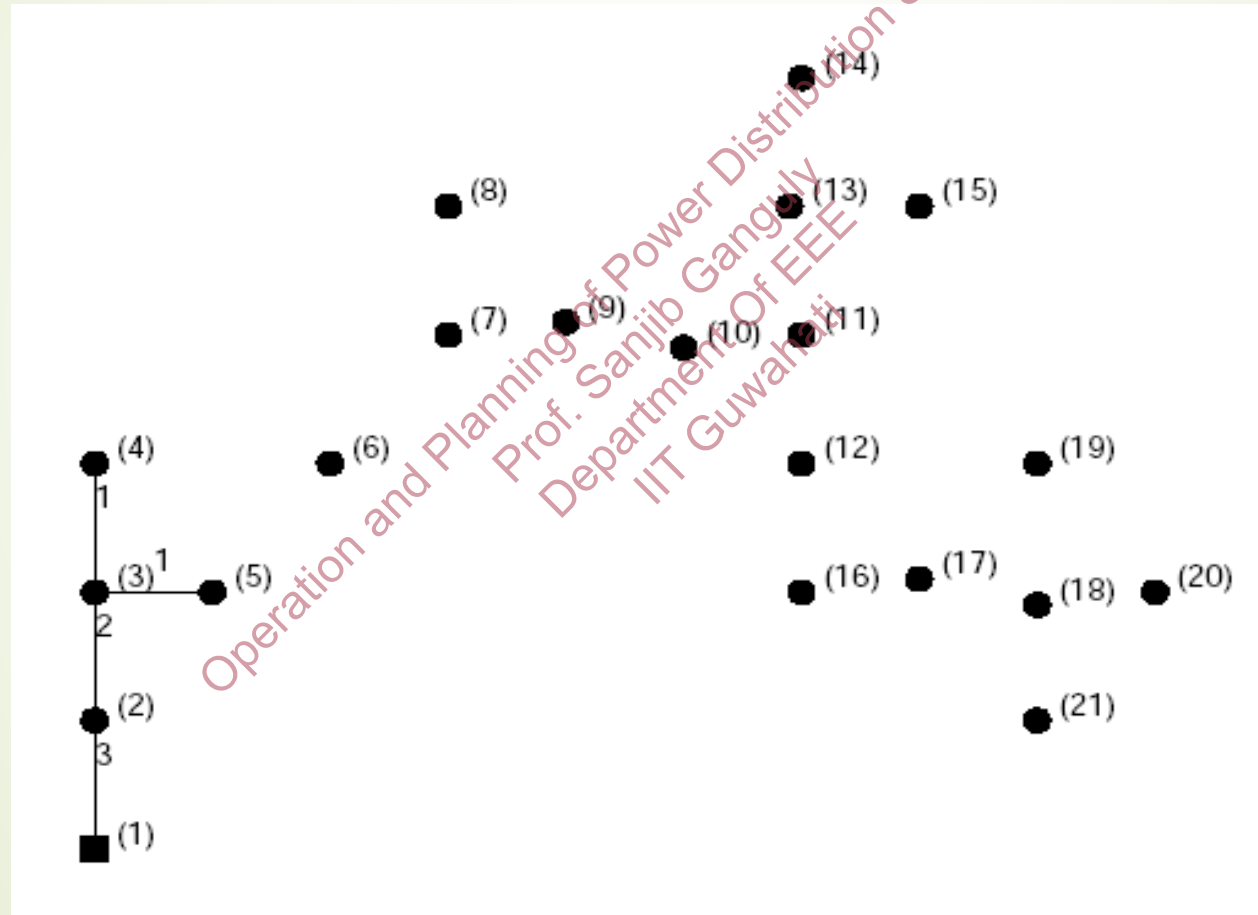
- 21-node system
- 54-node system
- 100-node system
- 182-node system

Operation and Planning of Power Distribution Systems
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Highlights of the test systems

- In all the systems, except the 182-node system, the substation location is specified at the node 1.
- The 21- and 182-node systems are with existing networks. Hence, they need expansion planning.
- For the 182-node system, there are two substations. They are located at 181 and 182 node.

21-node system: Locations of nodes



Data of the 21-node system

A	B	C	D	E	F	G	H
1	1	1.0	1.0	0	0	1	1.04
2	0	2.0	1.0	200	50	1	-
3	0	3.0	1.0	100	20	1	-
4	0	4.0	1.0	150	60	1	-
5	0	5.0	2.0	200	50	1	-
6	0	4.0	3.0	250	80	3	-
7	0	5.0	4.0	50	5	1	-
8	0	6.0	4.0	100	20	1	-
9	0	5.1	5.0	200	100	5	-
10	0	4.9	6.0	500	200	1	-
11	0	5.0	7.0	900	200	1	-
12	0	4.0	7.0	100	20	1	-
13	0	6.0	6.9	100	20	1	-
14	0	7.0	7.0	200	50	4	-
15	0	6.0	8.0	100	50	1	-
16	0	3.0	7.0	400	100	1	-
17	0	3.1	8.0	750	90	1	-
18	0	2.9	9.0	100	40	1	-
19	0	4.0	9.0	100	40	1	-
20	0	3.0	10.0	100	40	1	-
21	0	2.0	9.0	100	40	1	-

A Index of node;

B Type of node (0 for load, 1 for substation);

C North coordinate of node;

D West coordinate of node;

E Active load of node (kW);

F Reactive load of node ($kVAr$);

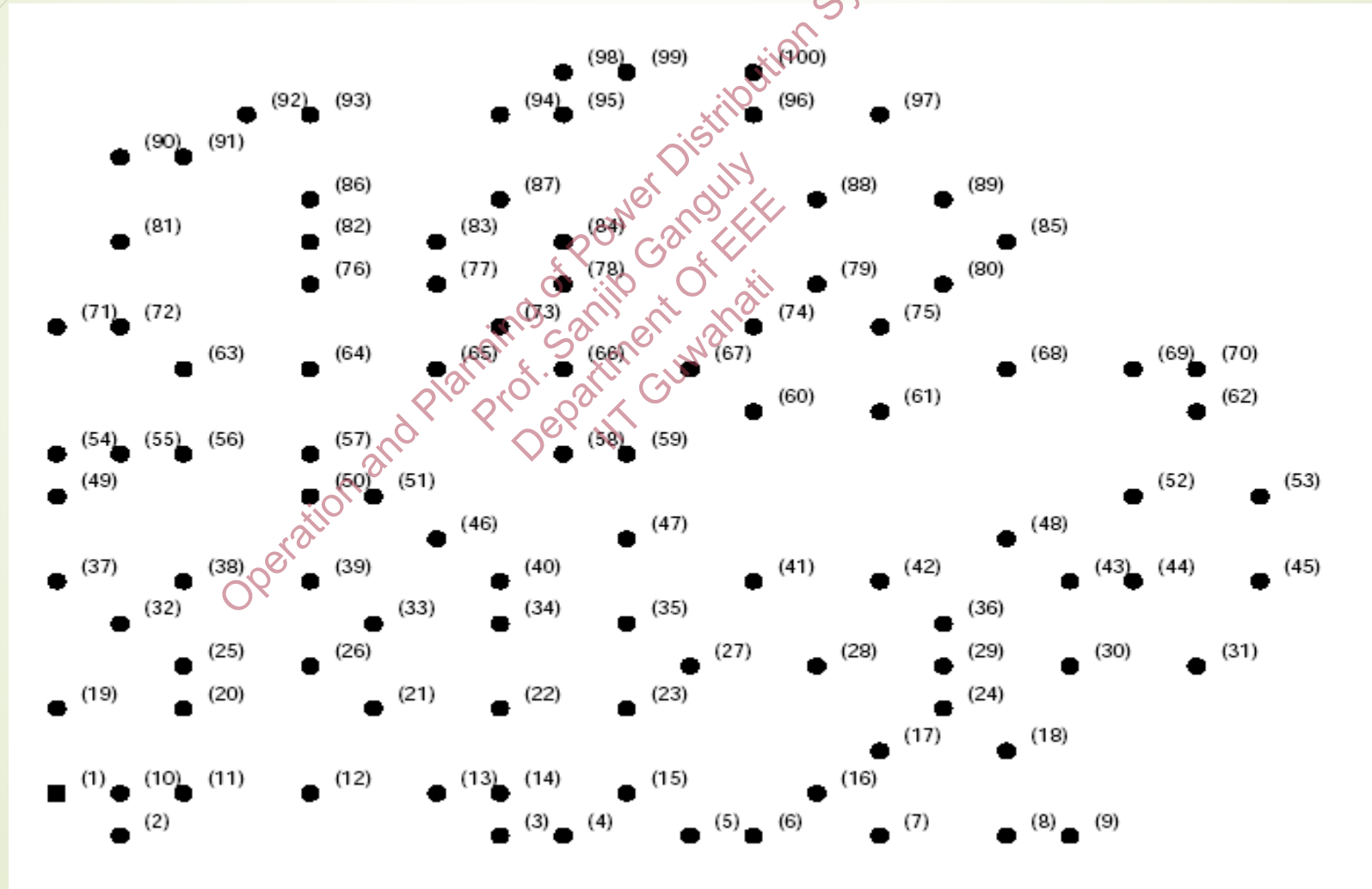
G Importance level of node;

H Node voltage (pu).

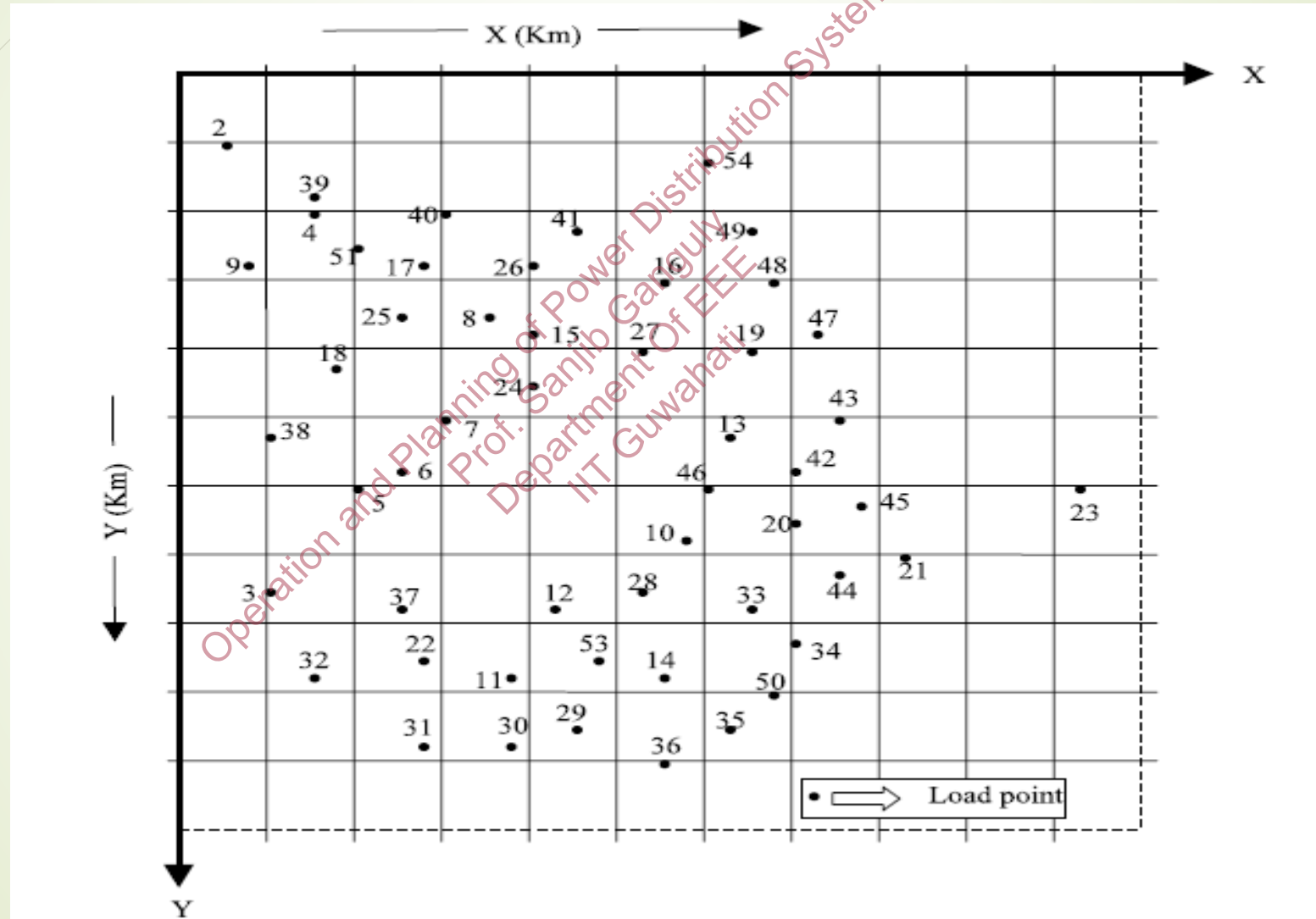
Conductor sizes for the 21-node system

Conductor type	Current rating (A)	Resistance (ohm/km)	Reactance (ohm/km)	Line/branch installation cost (\$/km)	Preventive maintenance cost (\$/km/year)	Corrective maintenance cost (\$/km/yr)	Failure rate (fault/km/yr)	Mean failure duration (h/fault/yr)
1	118	1.6118	0.4853	32126.23	1733.54	6.51	0.2	0.33
2	158	1.0145	0.4679	32321.31	1733.54	6.51	0.2	0.33
3	214	0.6375	0.4505	32653.55	1733.54	6.51	0.2	0.33
4	250	0.5205	0.4428	32780.81	1733.54	6.51	0.2	0.33
5	287	0.4019	0.4331	33378.78	1733.54	6.51	0.2	0.33
6	334	0.3184	0.4237	33752.81	1733.54	6.51	0.2	0.33
7	453	0.2006	0.4026	34100	1733.54	6.51	0.2	0.33
8	179	0.8220	0.3037	43000.00	218.77	1.09	0.00625	0.01
9	362	0.2646	0.2567	45476.95	218.77	1.09	0.00625	0.01

100-node system: Locations of nodes



54-node system: Locations of nodes



Conductor sizes for the 54- and 100- node systems

Conductor type	Current rating (A)	Resistance (ohm/km)	Reactance (ohm/km)	Branch installation cost (\$/km)	Preventive maintenance cost (\$/km/year)	Corrective maintenance cost (\$/km/year)	Failure rate (fault/km/yr)	Mean failure duration (h/fault/yr)
1	150	0.5762	0.5184	10000	533.54	6.51	0.1824	10.75
2	230	0.4724	0.2875	15000	533.54	6.51	0.1216	8.95

Conductor sizes for the 182-node system

Conductor type	Current rating (A)	Resistance (ohm/km)	Reactance (ohm/km)	Branch installation cost (\$/km)	Failure rate (fault/km/yr)	Mean failure duration (h/fault/yr)
1	255	0.2570	0.0870	135040	0.096	10.75
2	515	0.1020	0.0950	148470	0.064	8.95

Mono-objective planning

- ❖ Optimization of the two objectives is done taken one at a time.
- ❖ PSO is used as solution strategy
- ❖ A performance comparison among three PSO variants is done using statistical tests.
- ❖ A novel encoding/decoding scheme for PSO and a branch conductor size selection algorithm is proposed and used as supporting subroutines for PSO.

Why PSO?

- ❖ Among the evolutionary algorithms, PSO has not been used so far for distribution system planning.
- ❖ The attractive features of PSO are easy implementation, effective memory use, ability to deliver solutions with less number of function evaluations, and an efficient maintenance of diversity.
- ❖ Genetic algorithm (GA) is the mostly used strategy for the distribution system planning problem. Comparison between GA and PSO shows that PSO has faster convergence in different complex problems.

PSO: An overview

- A multi-point search technique developed by Kennedy and Eberhart
- Search starts with a population of search points called particle
- Each particle is encoded by a position vector
- Position is updated by velocity in successive iterations
- Velocity is updated by particle's own previous best value and by following the velocity of the group leader

Velocity and position update equations of PSO

$$U_{ij}^{iter+1} = U_{ij}^{iter} + \varphi_1 rn_1 (pbest_{ij}^{iter} - S_{ij}) + \varphi_2 rn_2 (gbest_j^{iter} - S_{ij})$$

$$S_{ij}^{iter+1} = S_{ij}^{iter} + U_{ij}^{iter+1}$$

$iter$ index for present iteration

U_{ij} velocity of the i-th particle j-th dimension

S_{ij} position of the i-th particle j-th dimension

φ_1, φ_2 learning constants

rn_1, rn_2 random numbers [0,1]

$pbest_{ij}$ best position of i-th particle's j-th dimension

$gbest_j$ global best position for j-th dimension discovered by whole population

PSO variants

(i) PSO with constriction factor (CF-PSO)

- A constriction factor is multiplied with the velocity update equation to prevent the velocity from going to very high values.

(ii) PSO with inertia weight (IW-PSO)

- An inertia weight is multiplied with the velocity of each particle to make a balance between local and global search.

(iii) Comprehensive learning PSO (CLPSO)

- Each dimension of a particle is updated separately by following an exemplar particle relatively fitter in the corresponding dimension so as to avoid the possibility of some dimensions of particle to worsen with simultaneous update of all dimensions.

Pseudocodes of mono-objective planning algorithm using PSO

Set the population size and maximum number of iterations (max_iter).
Generate initial population of particles using proposed encoding scheme.

Decode all particles by proposed decoding scheme and find out their objective function value with the chosen objective function.

For $iter=1, \dots, max_iter$

 Update velocity and position vectors of each particle

 Decode each particle and assign branch conductor sizes;

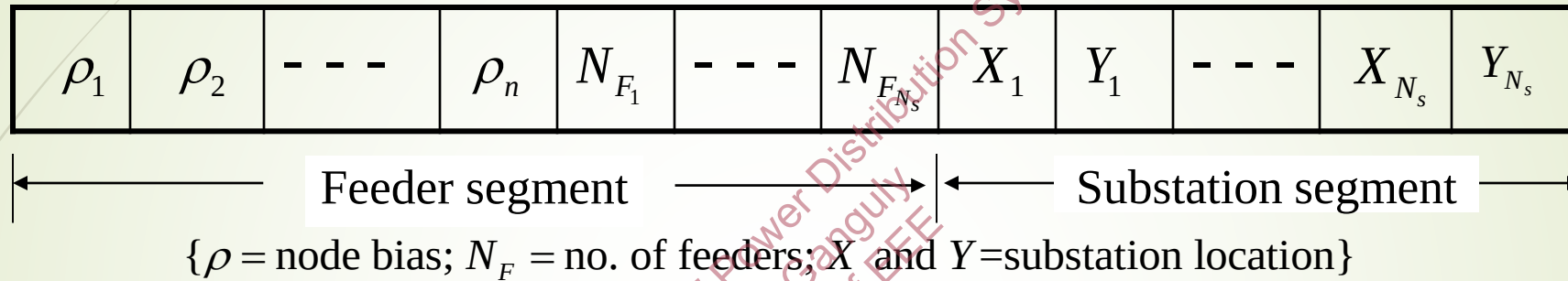
 Find out objective function for each particle;

 Preserve best particle that has superior fitness (objective function value) with no constraint violations, i.e., *elitist strategy*;

Endfor

The best particle most likely represents the optimal solution, i.e., network topology and conductor sizes.

Particle encoding/decoding scheme



Particle decoding scheme

- ✓ Network structure (feeder routes) is obtained with cost-biased decoding using the node bias information.
- ✓ Number of nodes that are directly connected with a substation is restricted to the number of feeders
- ✓ Substation location is obtained from the substation segment

Pseudocodes for the cost-biased decoding scheme

```

Let  {Q}: Nodes of branches existing in the network
     {R}: Nodes to be connected with the existing network
     {as} and {ae}: Start and end nodes of existing branches, respectively
While (R != null)
  For i=1,...,length(Q)
    For j=1,...,length(R)
      If B(Q(i),R(j))=1  \ \ B: node connectivity matrix [ its element=1
                           when connectivity between two node exists]
        C(i,j)=D(Q(i),R(j))* $\rho$ (j) [D: distance,  $\rho$  : node bias]
      Endif
    Endfor
  Endfor
  {Find the minimum element of C and corresponding Q(i) and R(j)}
  Update {as} $\leftarrow$ {as,Q(i)}; Update {ae} $\leftarrow$ {ae,R(j)};
  Update {Q} $\leftarrow$ {Q,R(j)}; delete R(j) from R
Endwhile

```

The advantage of the cost-biased decoding is that it always creates connected radial network.

Pseudocodes for conductor size selection

- Set same (randomly chosen) branch conductors to all branches for a solution network represented by a particle.
- Perform load flow to determine power flow in all branches of network.
- Assign conductor sizes to each branch rated immediately above the respective branch flow and obtain a set of branch conductors for the network, say, $\{cond_old\}$.
- Perform load flow and calculate the objective function of the solution network.
- Generate an integer random number rn , less than total number of branches of the network.

For $j=1, \dots, rn$

Change conductor size of branch j by higher rated conductor size than $cond_old(j)$;

Endfor

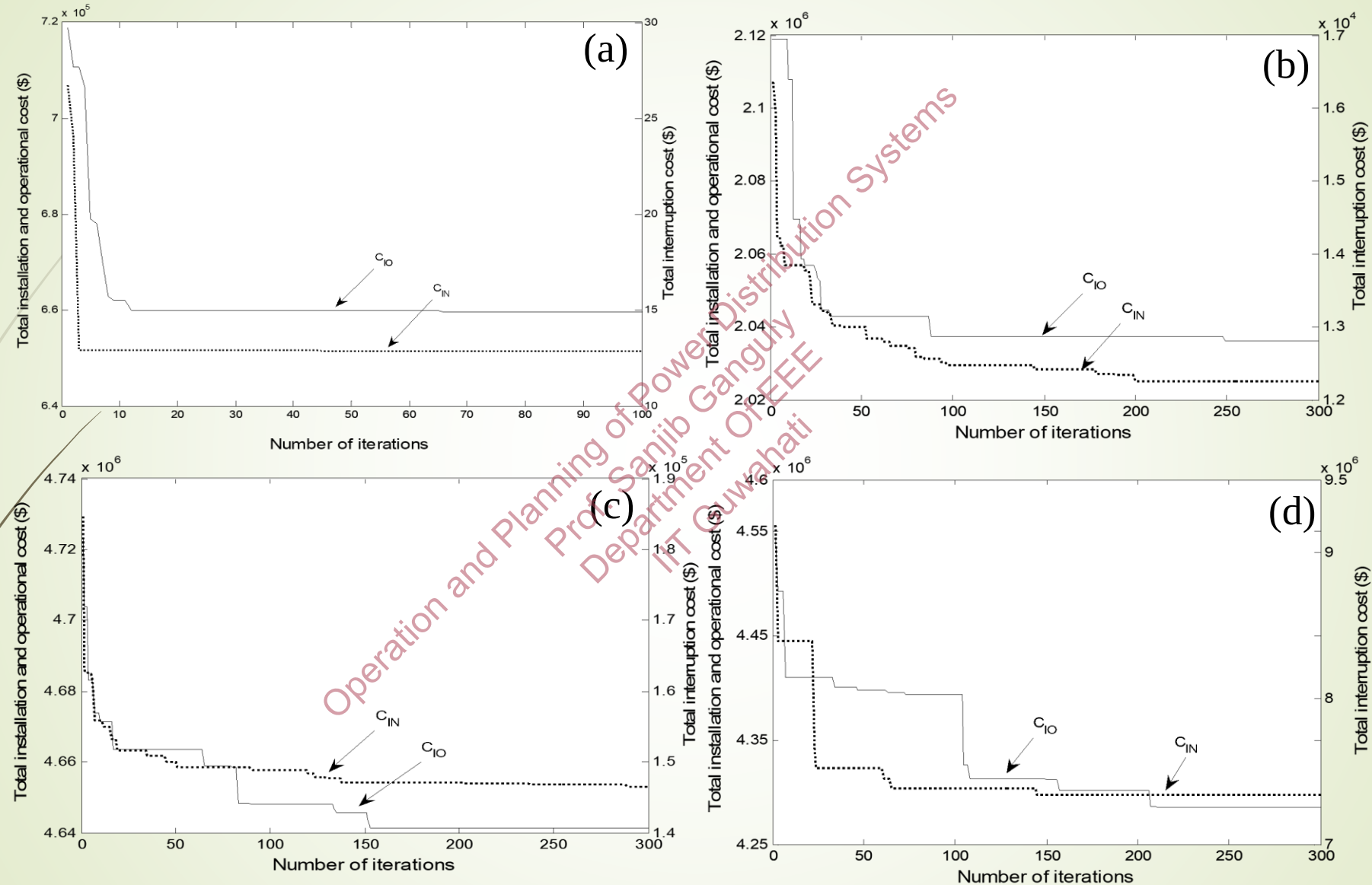
- Let the new set of conductor sizes for the network is $\{cond_new\}$.
- Perform load flow and calculate objective function for $\{cond_new\}$.
- If new objective function value is better than old, accept the set $\{cond_new\}$, else retain the set $\{cond_old\}$.

Constraint handling techniques

- ❑ Power balance constraint is automatically satisfied by load flow.
- ❑ Substation capacity is chosen as per the total load demand.
- ❑ Branch capacity is satisfied by the conductor size selection algorithm.
- ❑ If voltage limit constraint is violated, the solution is penalized such that its influence on other particles becomes very weak. A penalty factor, computed as the product of absolute value of maximum node voltage deviation and a very high integer number, is added with the objective function.
- ❑ The radiality constraint is always satisfied by the proposed decoding scheme.

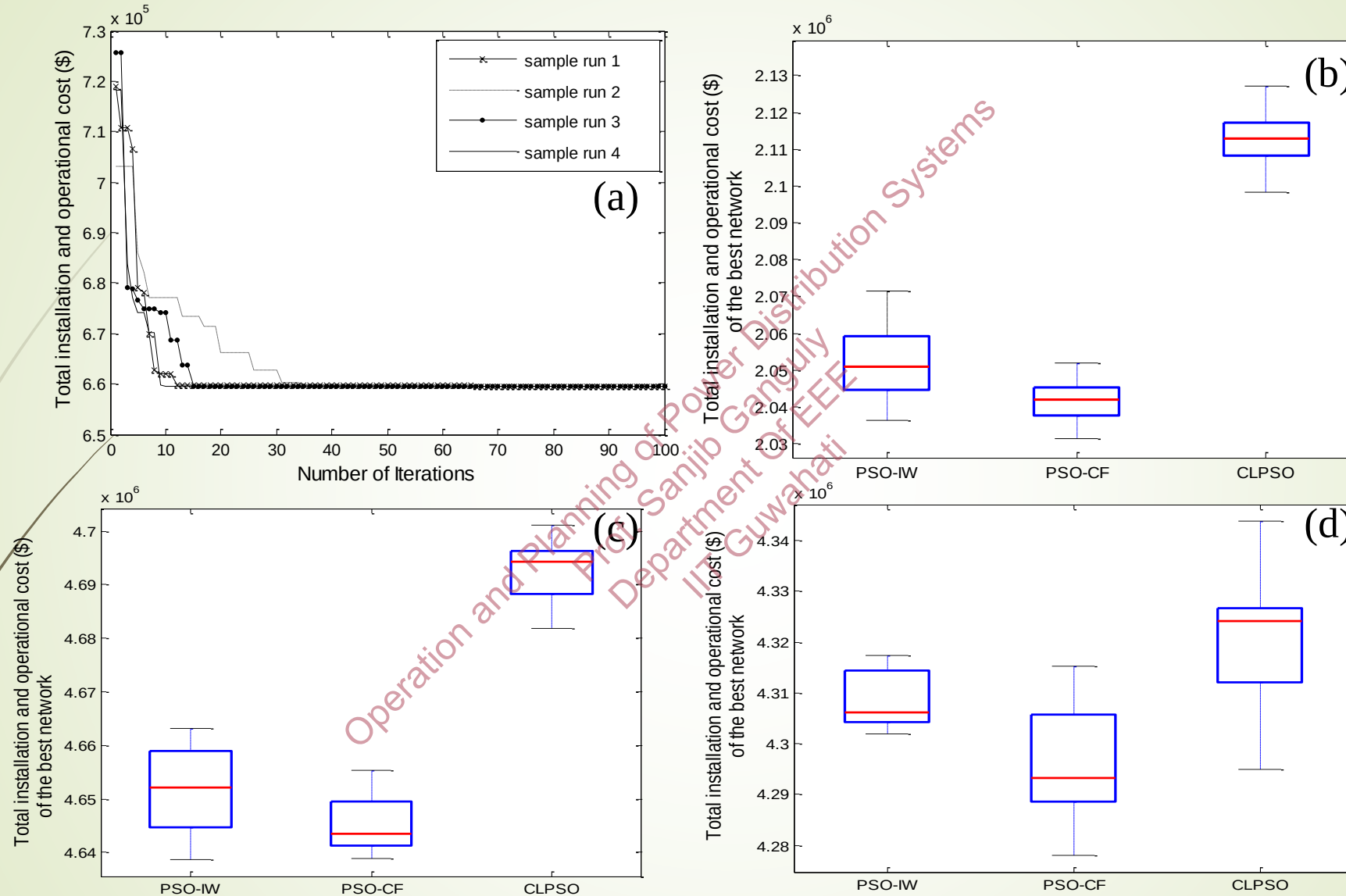
Typical convergence curves of the mono-objective planning

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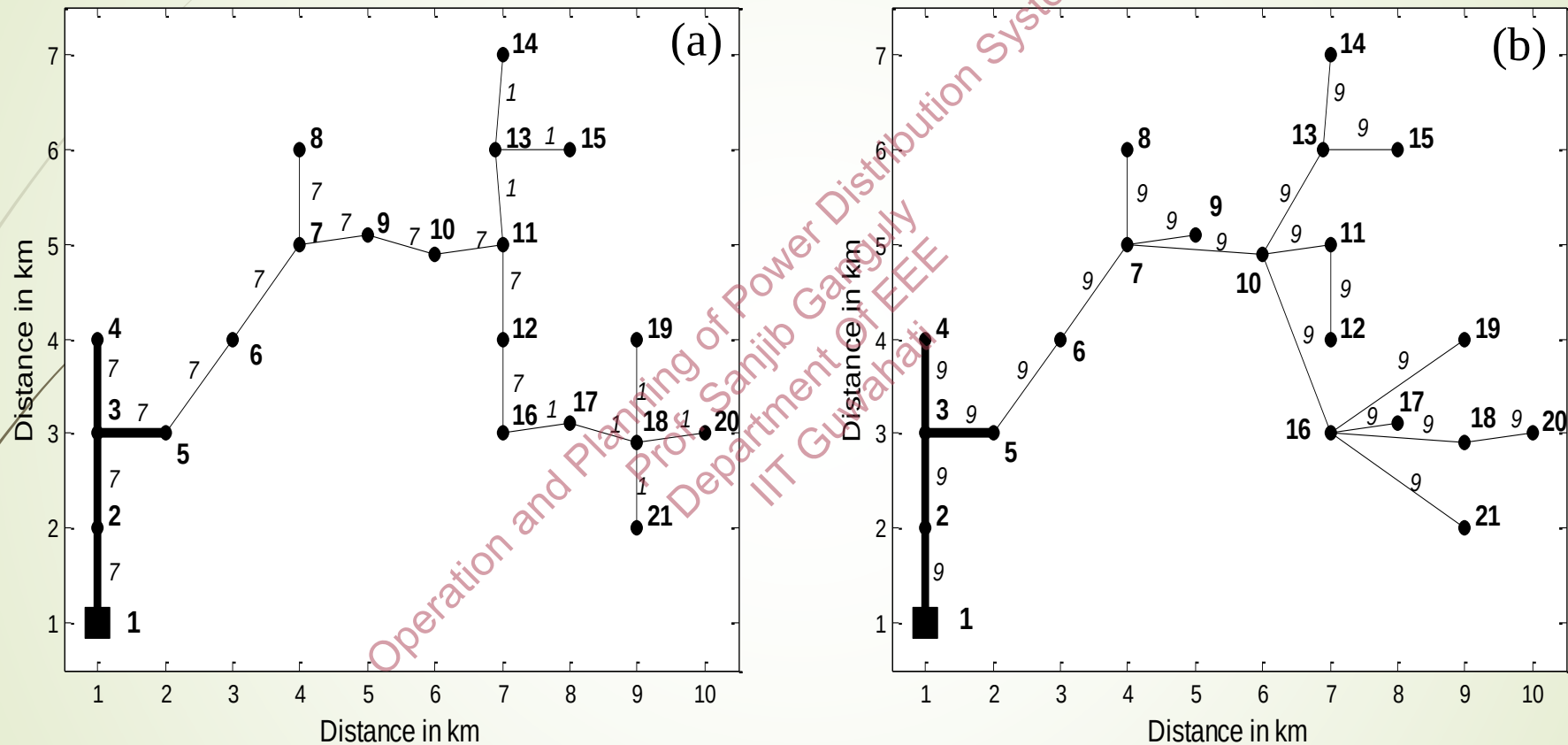
Results of statistical test

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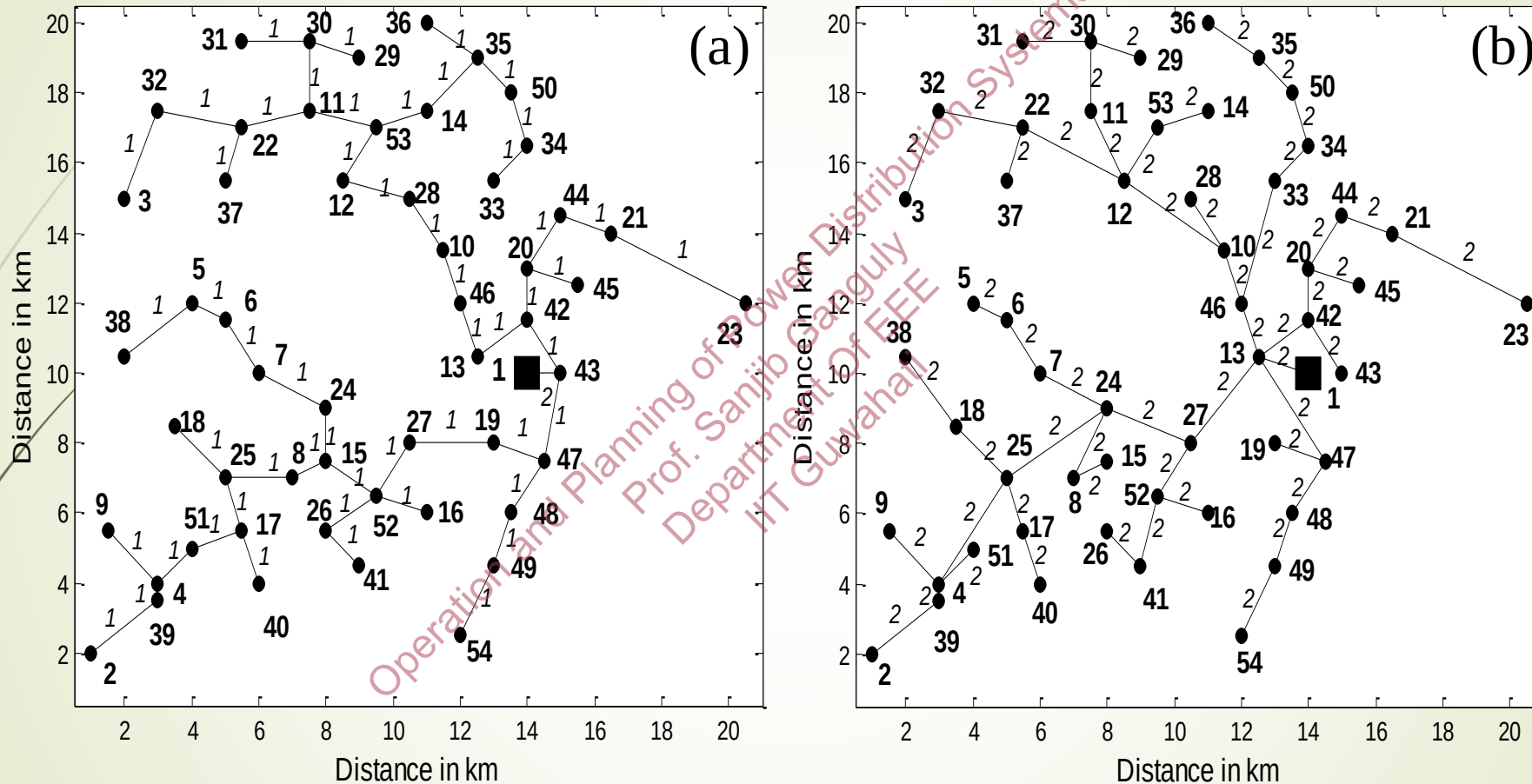
Legend: (a) results for the 21-node system in multiple runs, (b) boxplots of the final solution for 54-node system, (c) boxplots of the final solution for 100-node system, and (d) boxplots of the final solution for 182-node system

Two solution networks of mono-objective planning for the 21-node system



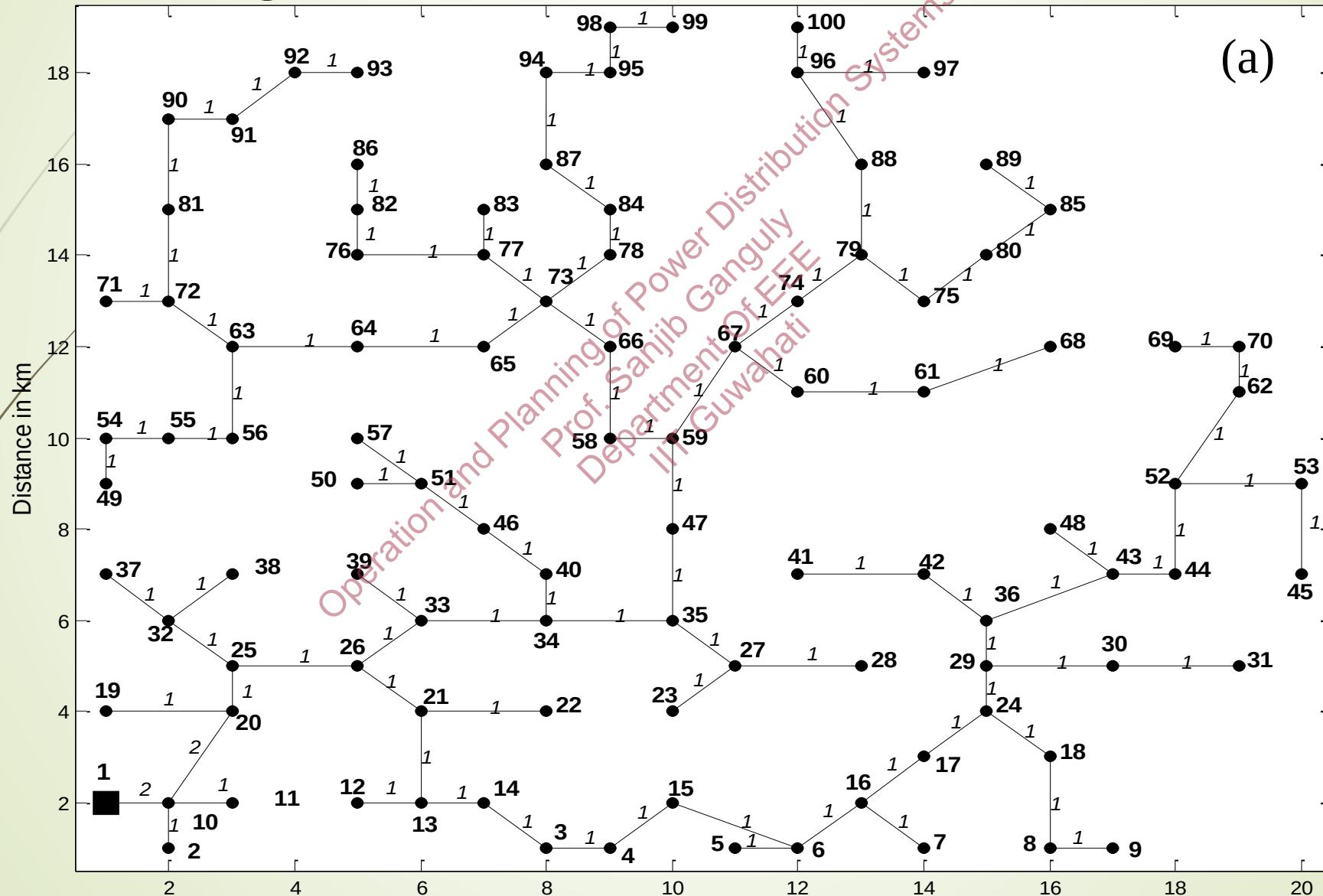
Legend: (a) most economical and (b) most reliable networks

Two solution networks of mono-objective planning for the 54-node system

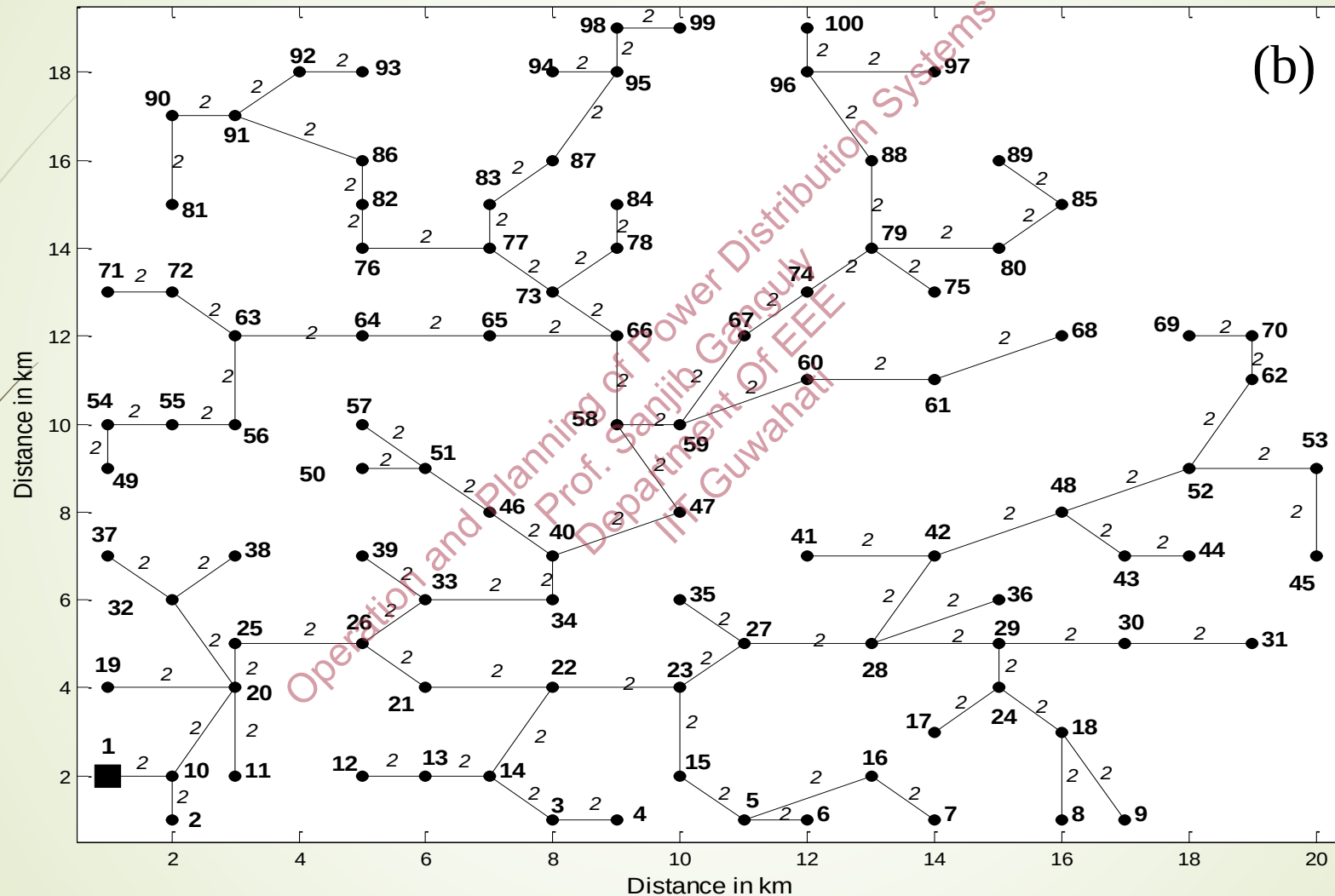


Legend: (a) most economical and (b) most reliable networks

Two solution networks of mono-objective planning for the 100-node system

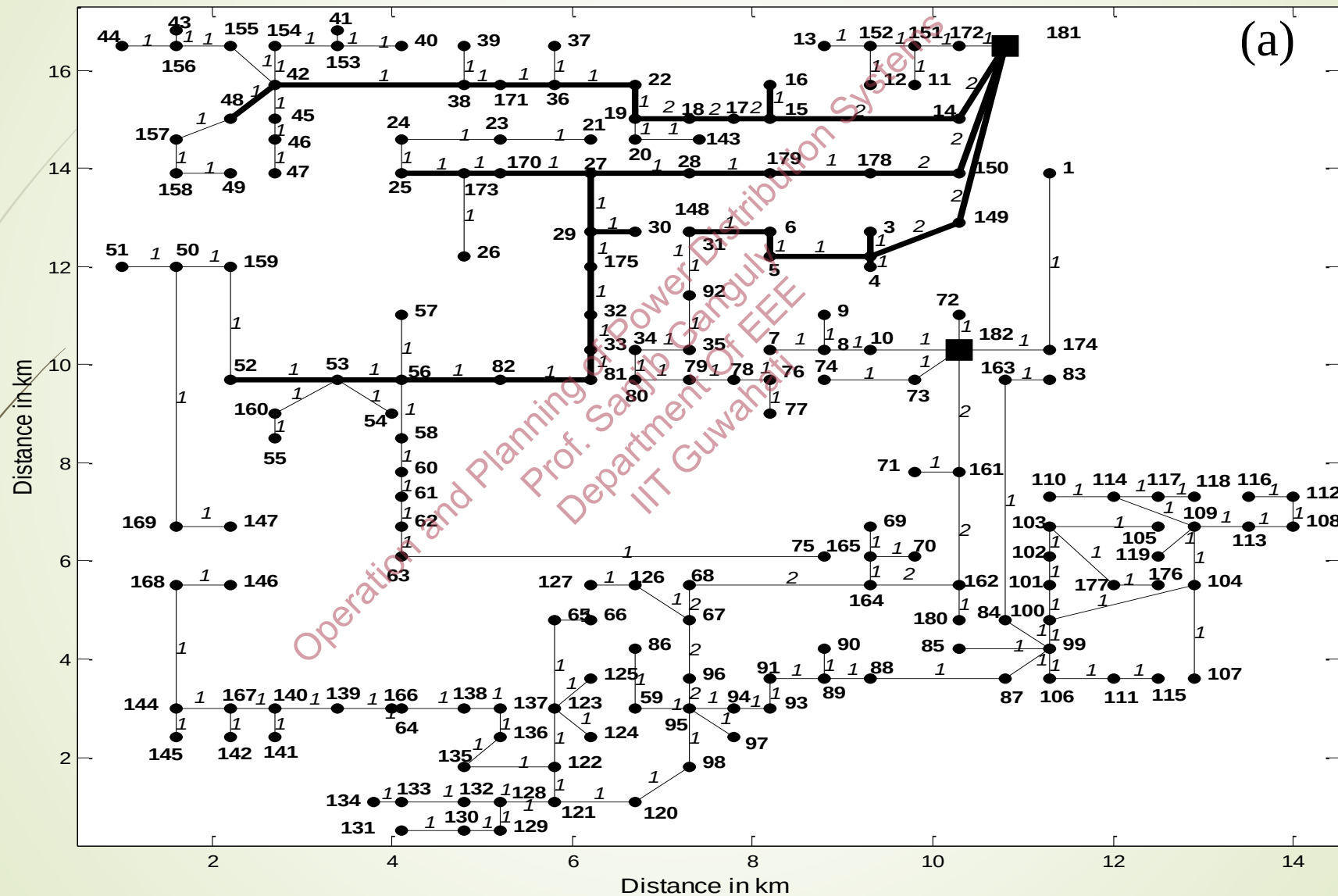


Two solution networks of mono-objective planning for the 100-node system

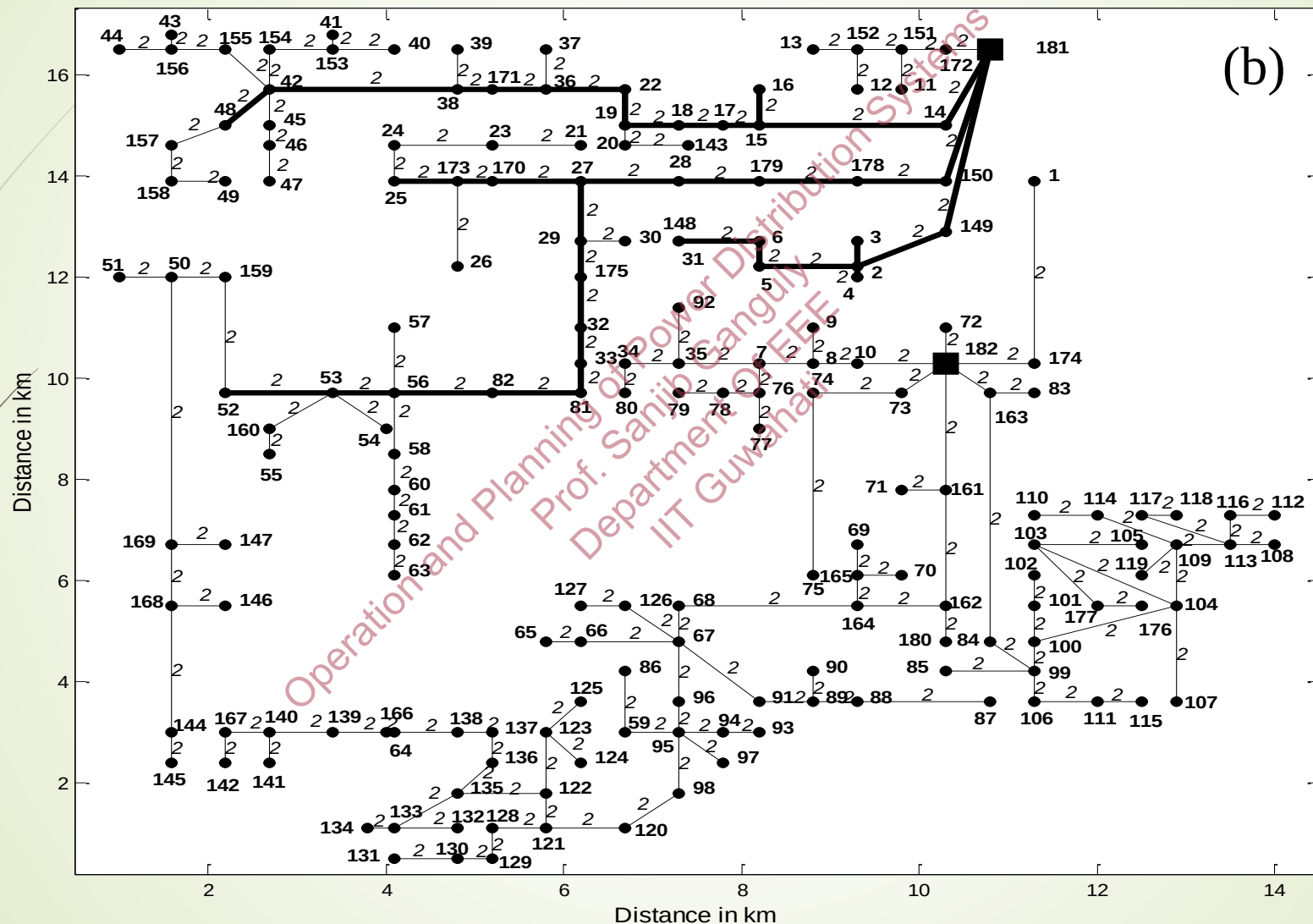


Legend: (a) most economical and (b) most reliable networks

Two solution networks of mono-objective planning for the 182-node system



Two solution networks of mono-objective planning for the 182-node system



Legend: (a) most economical and (b) most reliable networks

Mono-objective vs. multi-objective optimization

- ❖ The objective functions for this planning, i.e., cost and reliability generally conflict with each other.
- ❖ There exists a set of trade-off solutions for the problem with conflicting objectives.
- ❖ A set of trade-off solutions can be obtained with simultaneous optimization of all objectives.
- ❖ Mono-objective optimization can not perform simultaneous optimization of multiple objectives. The multi-objective optimization is required for such type of optimization.

Multi-objective planning

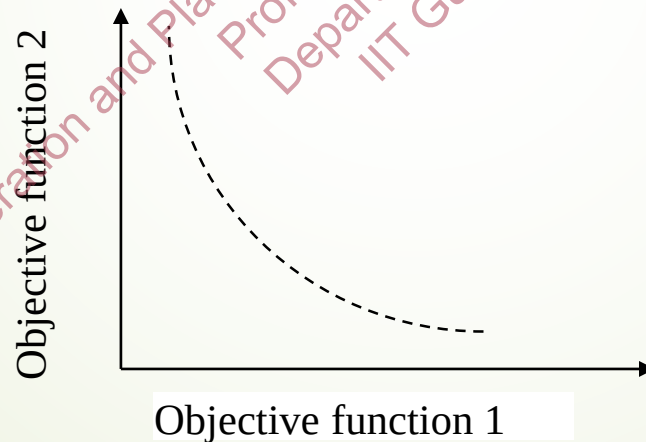
- ❖ Simultaneous optimization of the objectives is done using Pareto-dominance principle.
- ❖ Strength Pareto Evolutionary Algorithm-2 (SPEA2), a multi-objective algorithm is used to extend PSO to multi-objective PSO (MOPSO).
- ❖ SPEA2-MOPSO based planning algorithm is used for both static and expansion planning

Pareto-dominance principle

The Pareto-dominance principle states that for an m objective optimization (say, minimization) problem, a solution x dominates solution y if:

for all i , $f_i(x) \leq f_i(y)$, and $\exists j$ such that $f_j(x) < f_j(y)$, $i = 1, \dots, m$.

A set of non-dominated solutions constitutes a Pareto-front.



Pareto-front of a two-objective minimization problem

Pseudocodes of SPEA2-MOPSO-based distribution system planning algorithm

Begin

Generate *initial population* by PSO encoding scheme;

Decode the *particles* to obtain *initial non-dominated solutions*;

Store them in *elite archive*;

Calculate *fitness of particles*;

iteration=1;

//*Population_size* = size of PSO population, //*Max_iter*= Maximum number of iterations

While *iteration* ≤ *Max_iter***For** *i*=1,...,*Population_size*

Update *velocity* and *position* of the particle according to PSO;

Decode *particle* to get the network topology;

Select *conductor size* using conductor size selection algorithm;

Calculate *objective functions* and assign *particle fitnesses* by SPEA2;

Endfor

Find out *non-dominated solutions* and update *elite archive* by SPEA2;

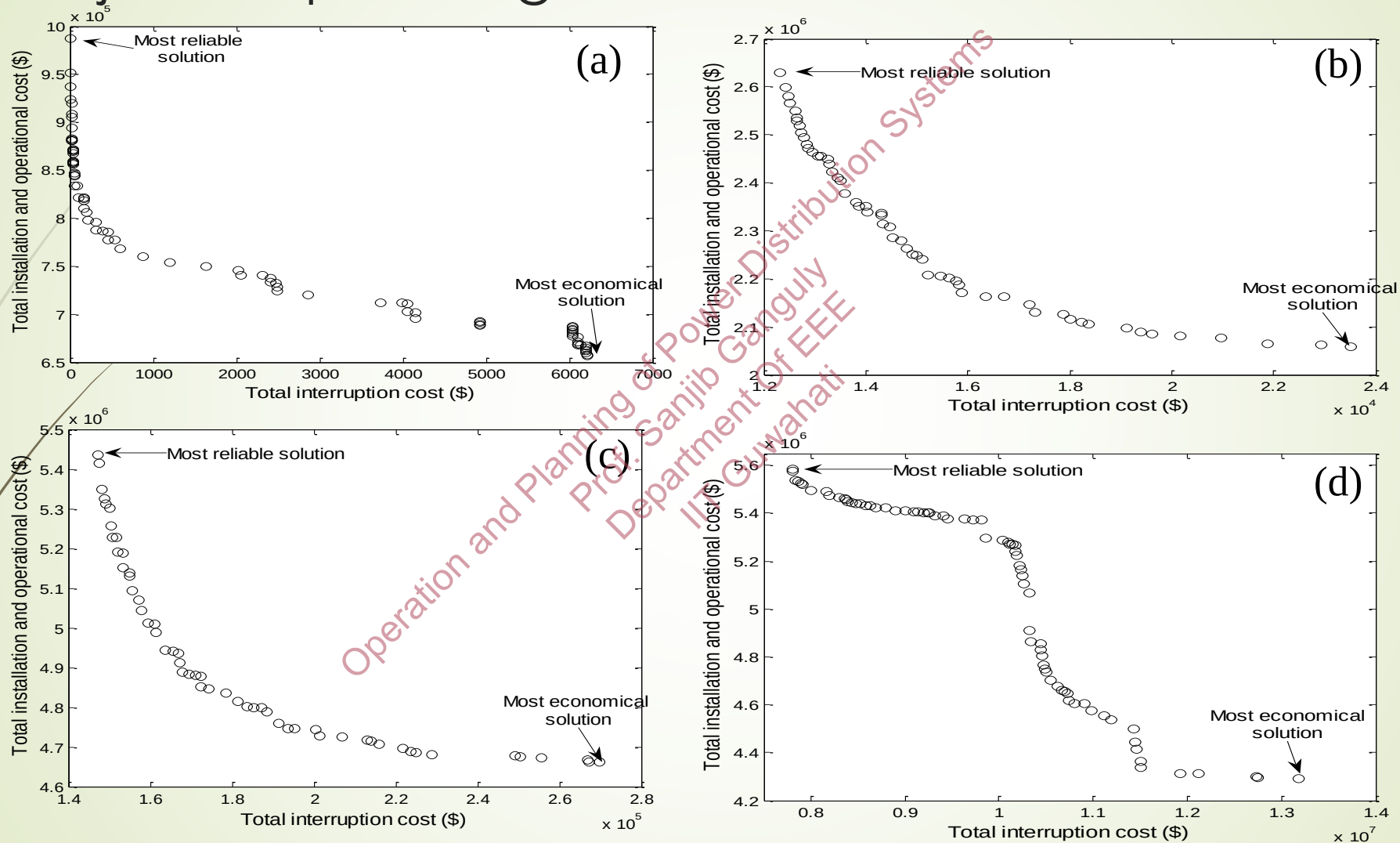
iteration=*iteration*+1;

Endwhile

Elite archive contains optimal network topologies and conductor sizes

End

The Pareto-approximation fronts obtained with multi-objective planning



Legends: (a) 21-, (b) 54-, (c) 100-, and (d) 182-node systems

Performance comparison with multi-objective GA (MOGA)-based planning

Solutions	Objective functions (MOGA [Carrano <i>et al.</i> <i>IEEE PWRD</i> , 2006])		Objective functions (SPEA2-MOPSO)	
	First	Second	First	Second
Most economical	6.7×10^5	843.79	6.66×10^5	818
Most reliable	17.07×10^5	7.71	15.4×10^5	16.1889

Qualitative comparison:

- The proposed encoding/decoding scheme always guarantees generation of connected radial networks.
- The implementation of the proposed algorithm is easier as there is no need of so many heuristic crossover and mutation operators.

Summary

- ❖ Both mono- and multi-objective planning algorithms are presented for static and expansion planning of distribution systems.
- ❖ The proposed modified cost-biased encoding/decoding scheme always generates connected radial network for the distribution systems.
- ❖ The performance assessment with several statistical tests indicates that the proposed algorithm is an effective tool that can be used for the optimization of large-scale distribution systems.

Multi-objective planning of electrical distribution systems using dynamic programming

Objectives:

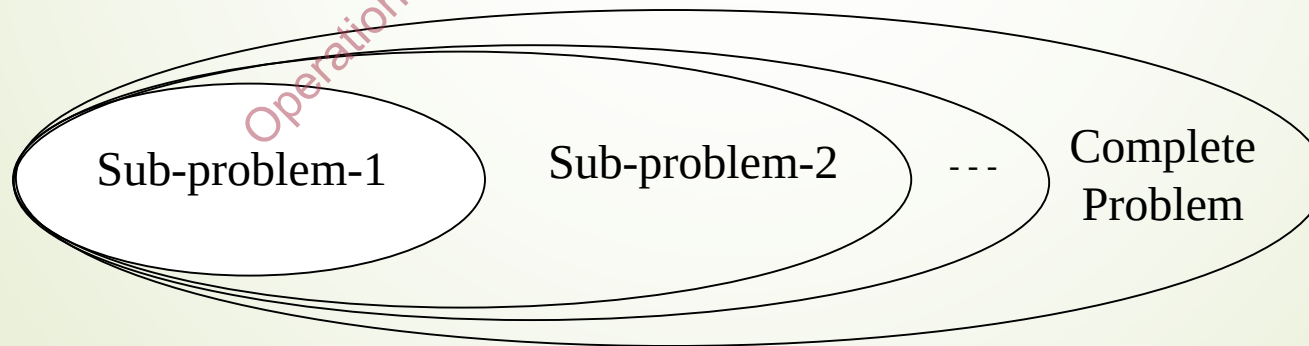
- ❑ Development of a dynamic programming-based approach for multi-objective planning of distribution systems
- ❑ To present a qualitative and quantitative performance comparison between the dynamic programming and the multi-objective evolutionary algorithm (MOEA)-based approaches such as:
 - SPEA2-MOPSO
 - MOGA [Carrano *et al.* IEEE PWRD, 2006]

Why Dynamic programming?

- Dynamic programming can solve non-linear, non-differentiable problems.
- Dynamic programming has not been used so far for the multi-objective planning of distribution systems.
- Comparison shows that the dynamic programming is much faster compared to the mixed integer programming [Boulaxis *et al.* IEEE PWRD, 2002].

Dynamic programming: An overview

- ❑ Two key ingredients of dynamic programming are optimal substructure and overlapping sub-problems.
- ❑ Firstly, the dynamic programming decomposes a multi-stage decision problem into several overlapping sub-problems. Then, it solves all the sub-problems recursively, in a bottom-up fashion.



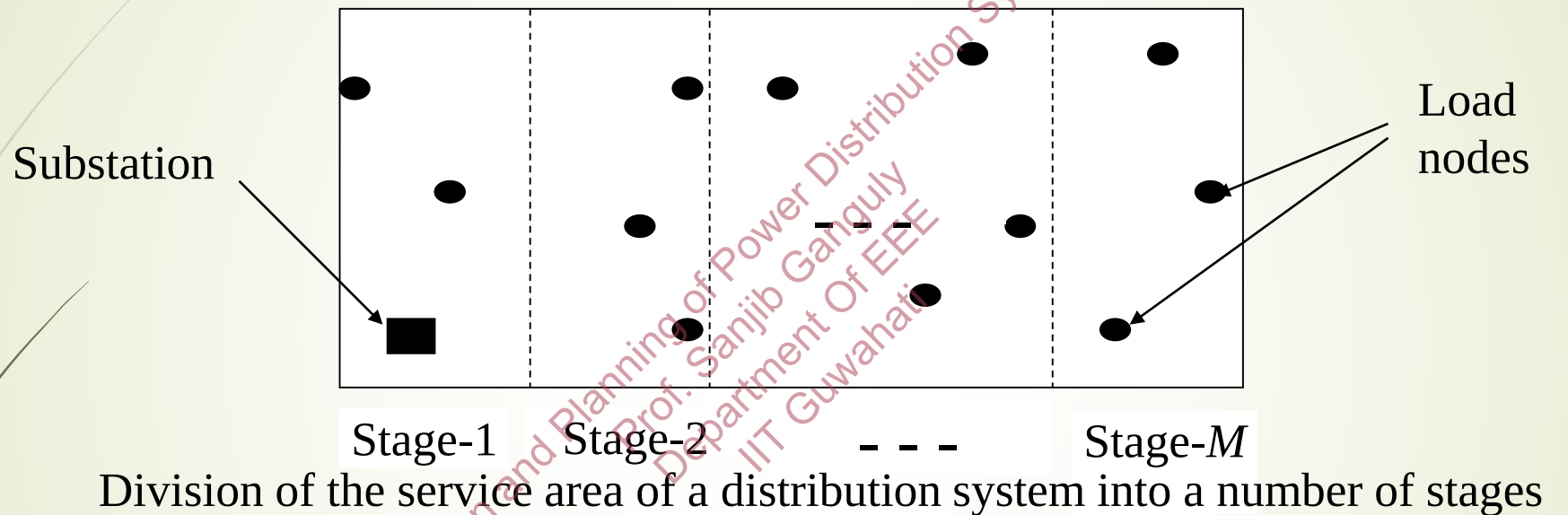
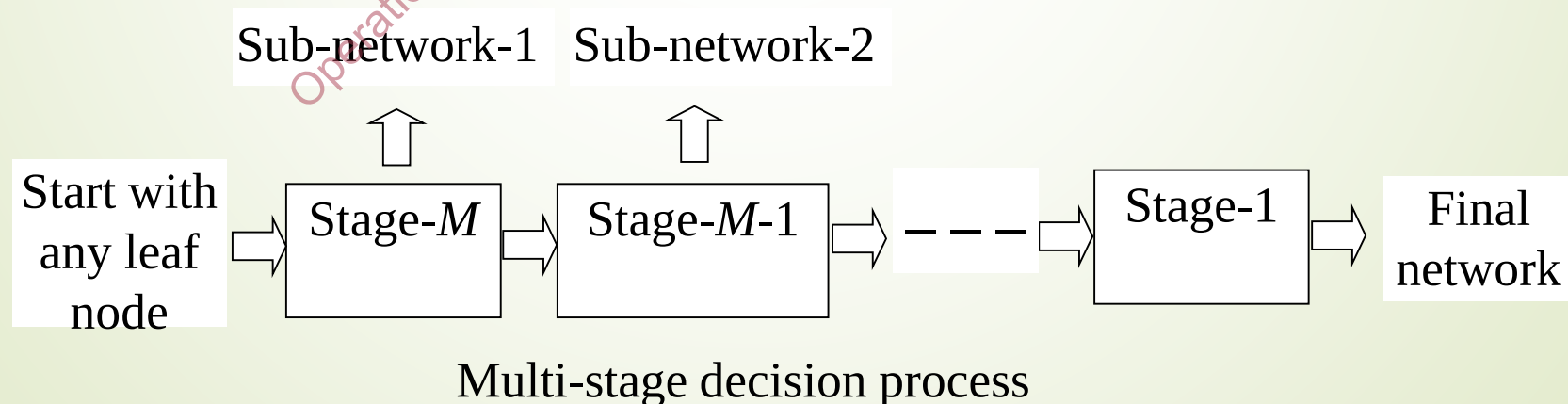
Decomposition of a problem into several overlapping sub-problems

Dynamic programming for multi-objective planning of electrical distribution systems

- ❖ Both the objective functions are functions of branch power flows which depend on the load demand of all the downstream nodes.
- ❖ Optimization of a branch/feeder route can be carried out after optimization of all its downstream branches.
- ❖ Network structure optimization and branch conductor size optimization are done with two approaches:
 - (i) Non-iterative two-step approach
 - (ii) Iterative two-step approach
- ❖ Non-dominated solutions are obtained with a weighted objective with different settings of weights

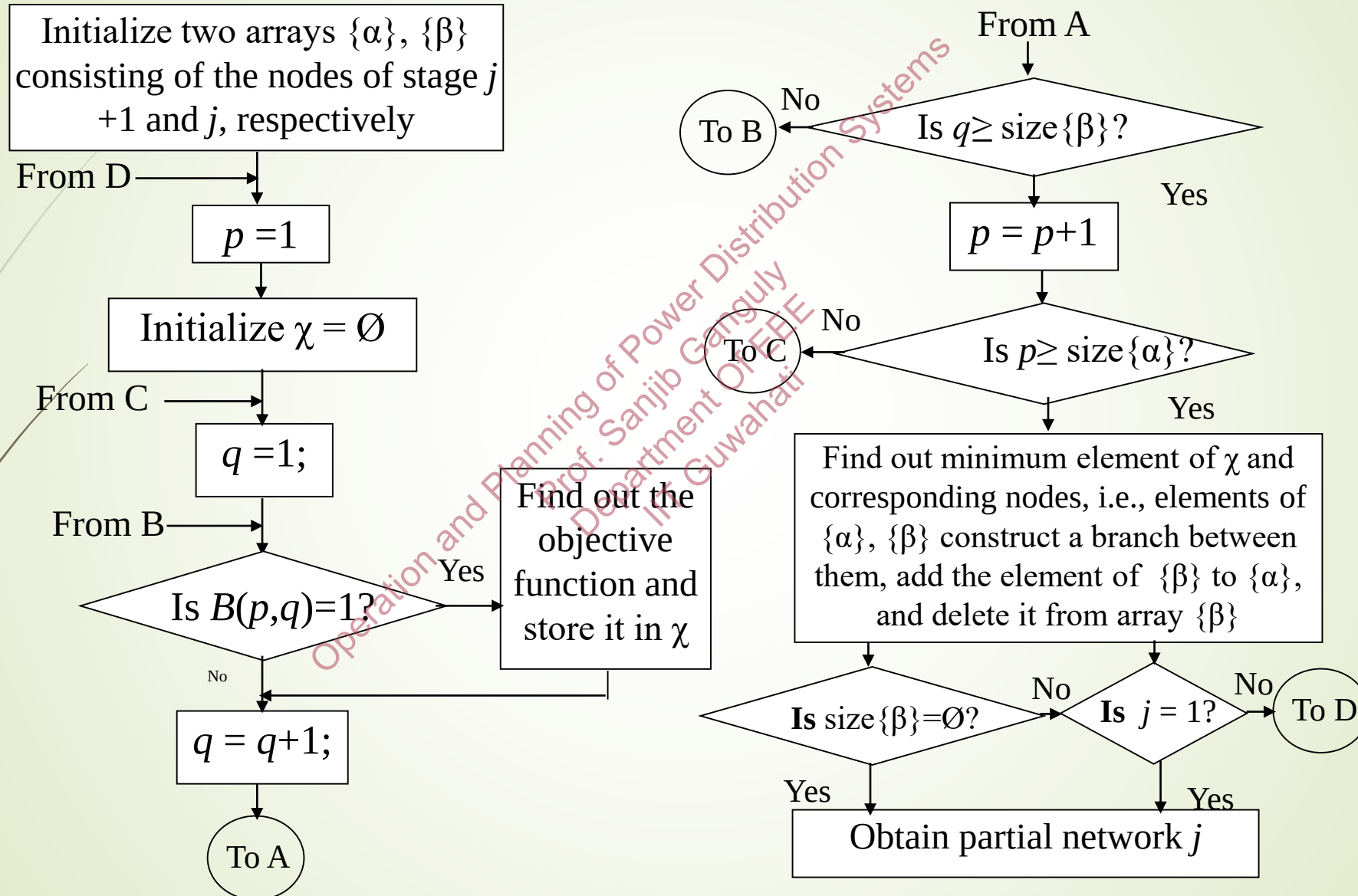
$$C_T = w_1 C_{IO}^{norm} + w_2 C_{Fa}^{norm}, \text{ such that } w_1 + w_2 = 1; [w_1, w_2 \text{ are pre-defined weights}]$$

Dynamic programming for multi-objective planning of electrical distribution systems



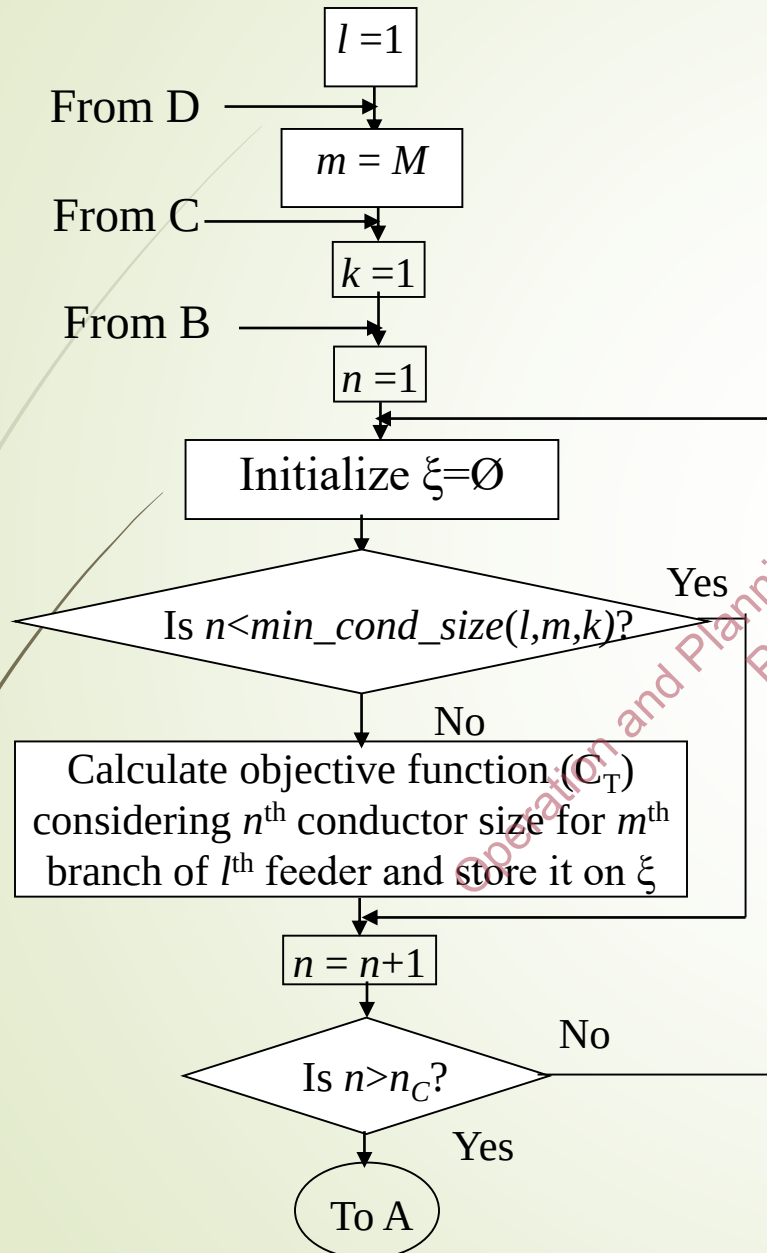
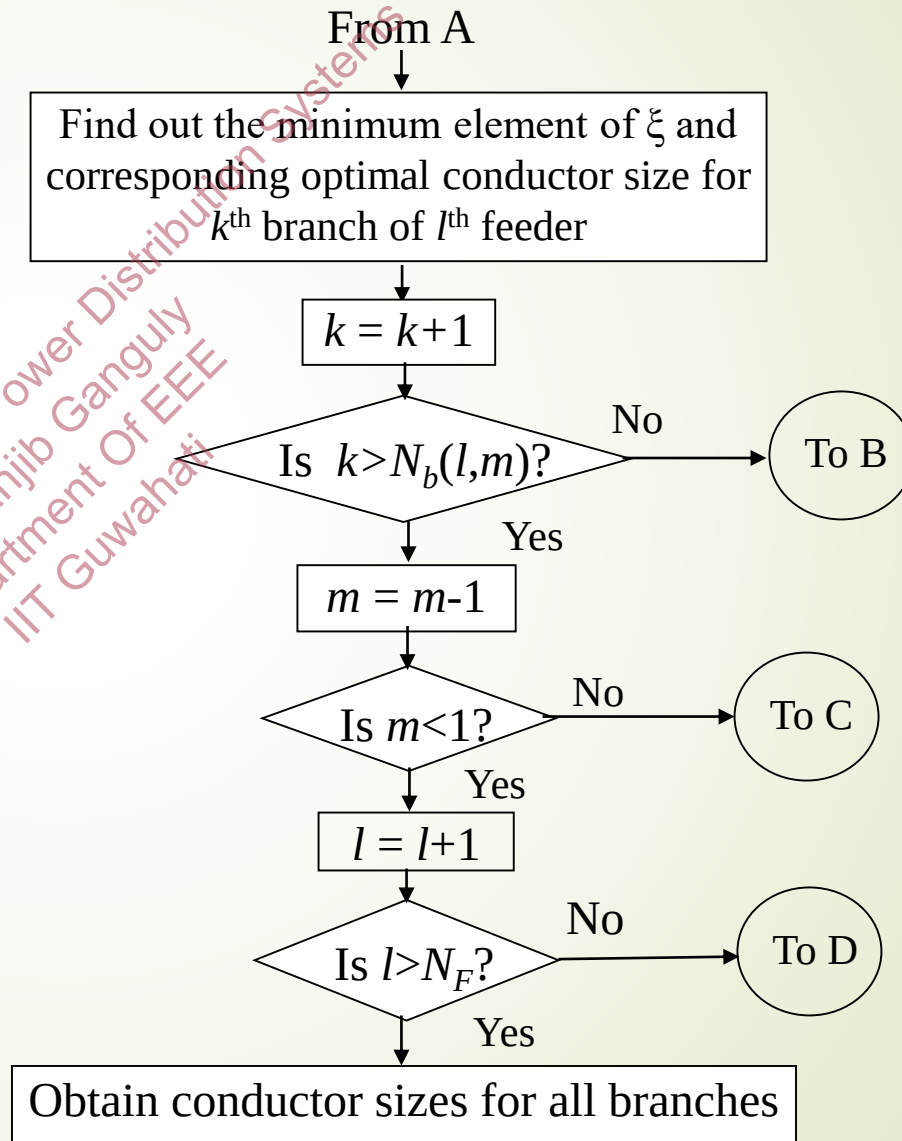
Network structure optimization

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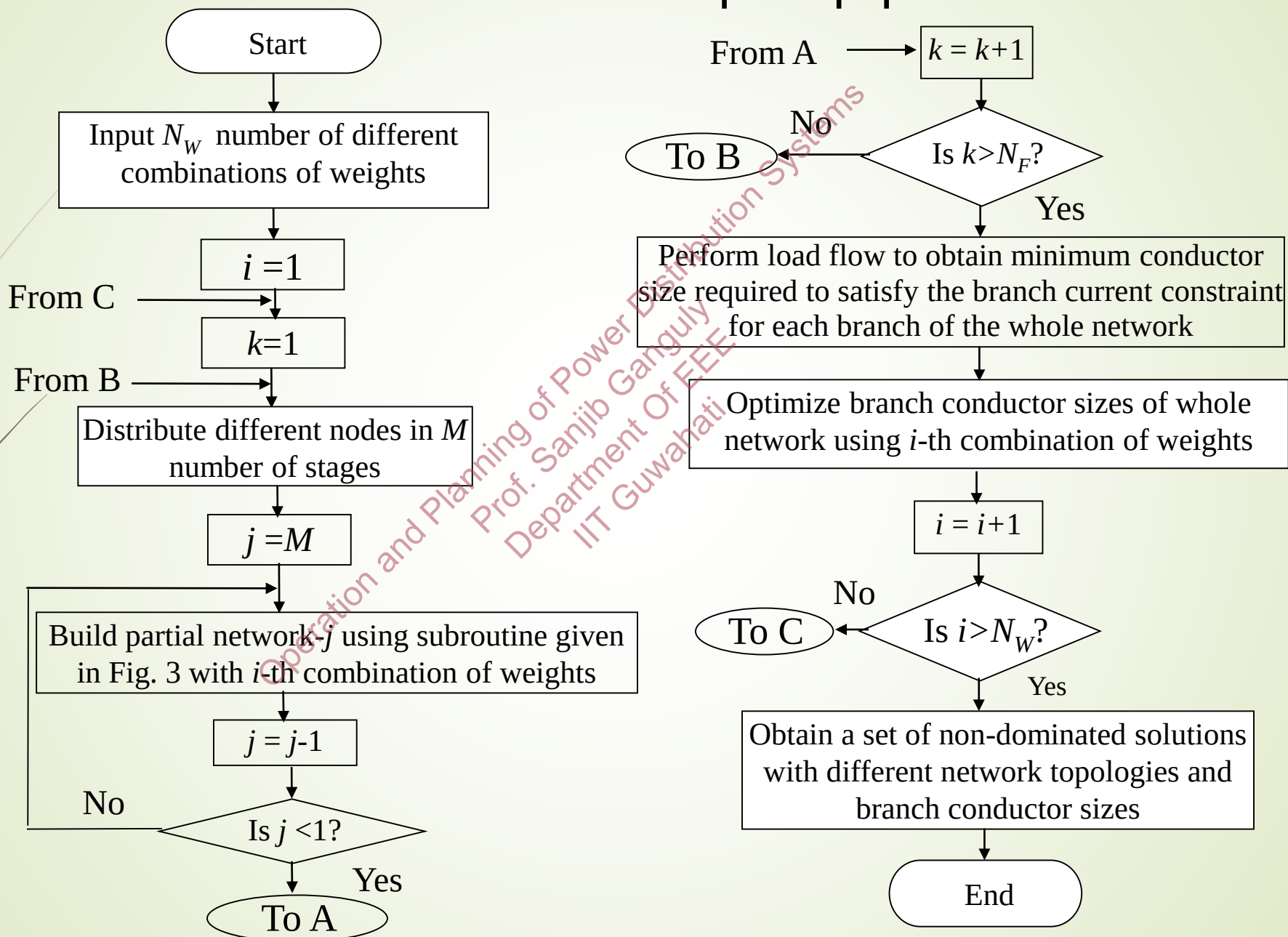
Branch conductor size optimization

54



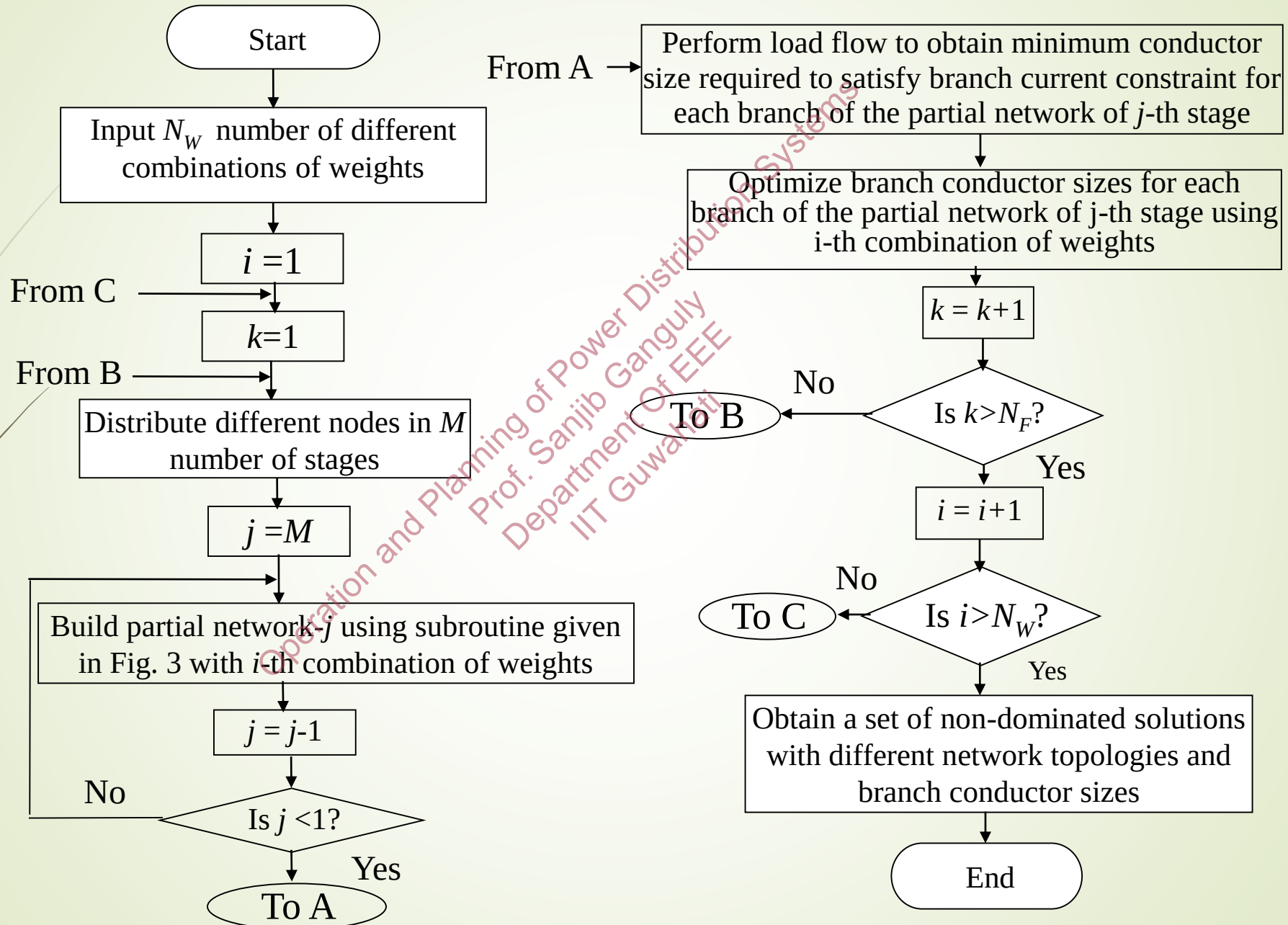
Non-iterative two-step approach

55

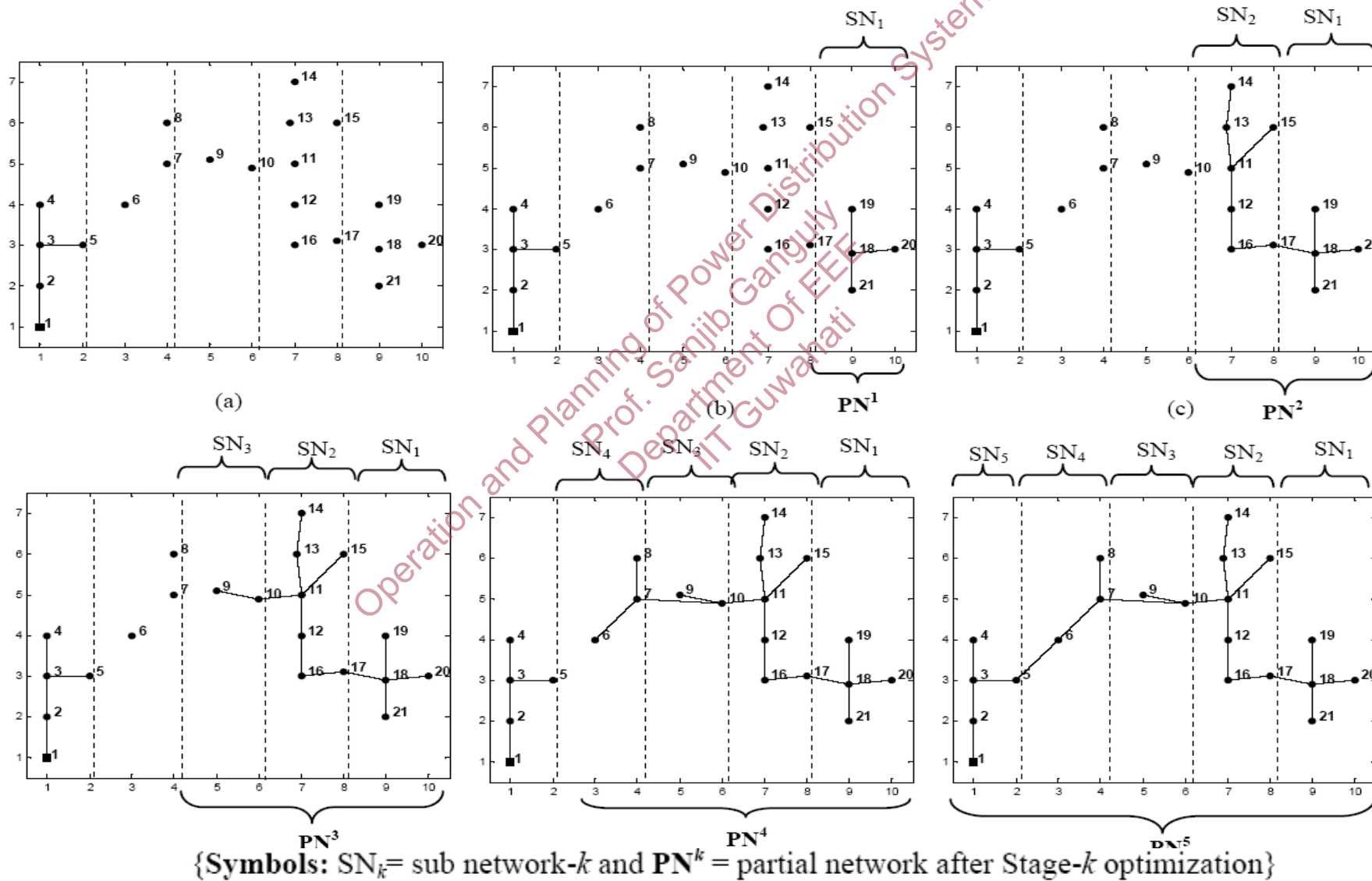


Iterative two-step approach

56

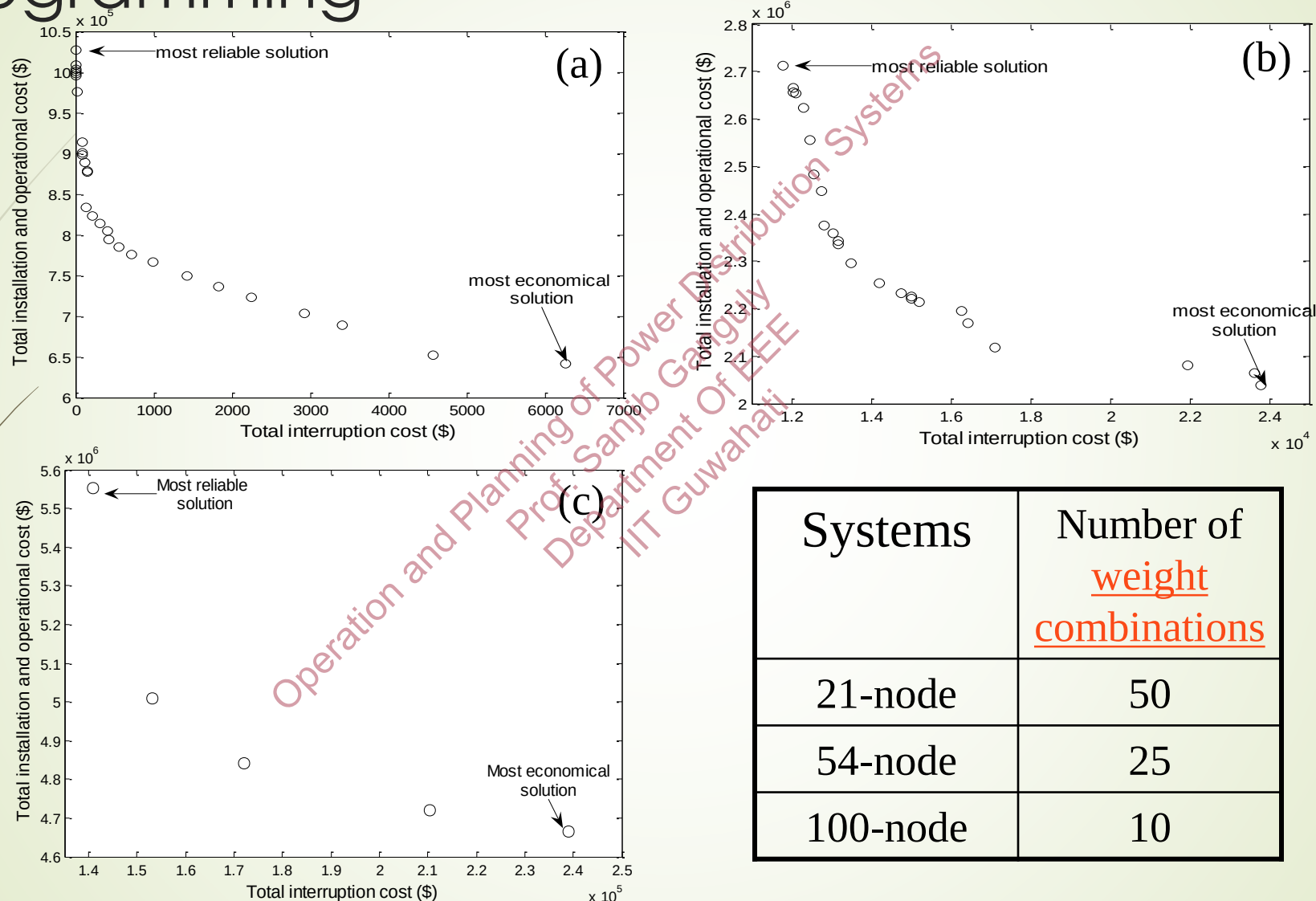


Stage by stage evolution of the network for 21-node system



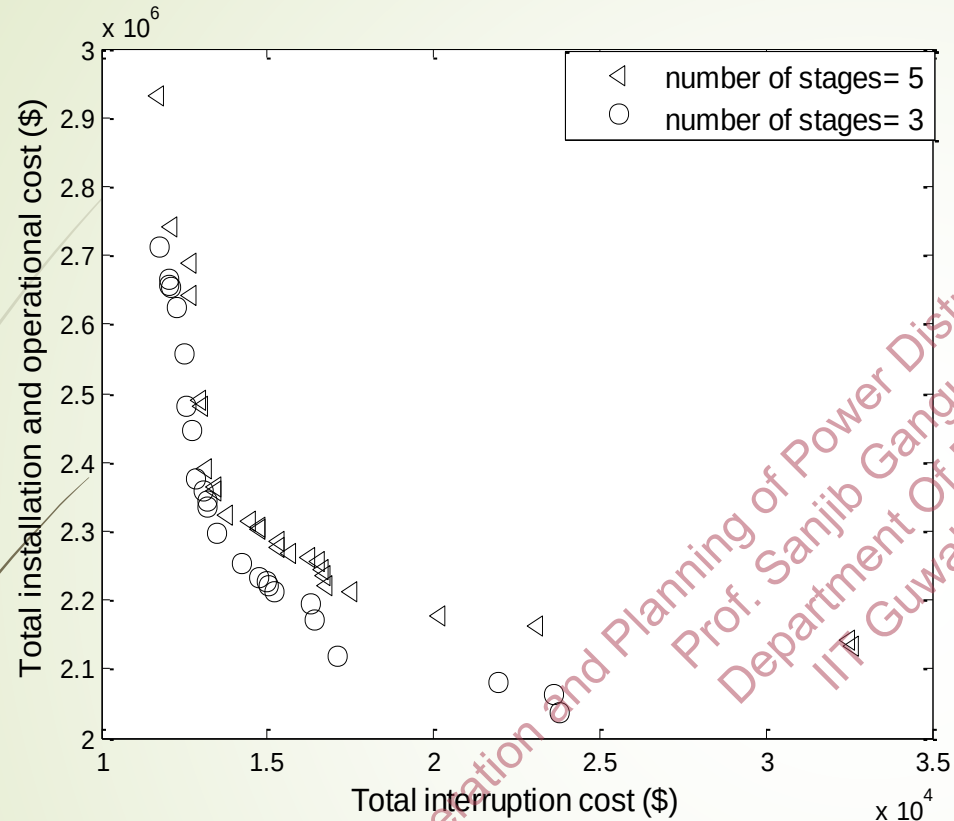
Pareto-approximation fronts obtained with dynamic programming

58



Legends: (a) 21-, (b) 54-, and (c) 100-node systems

Sensitivity test (with different number of stages)

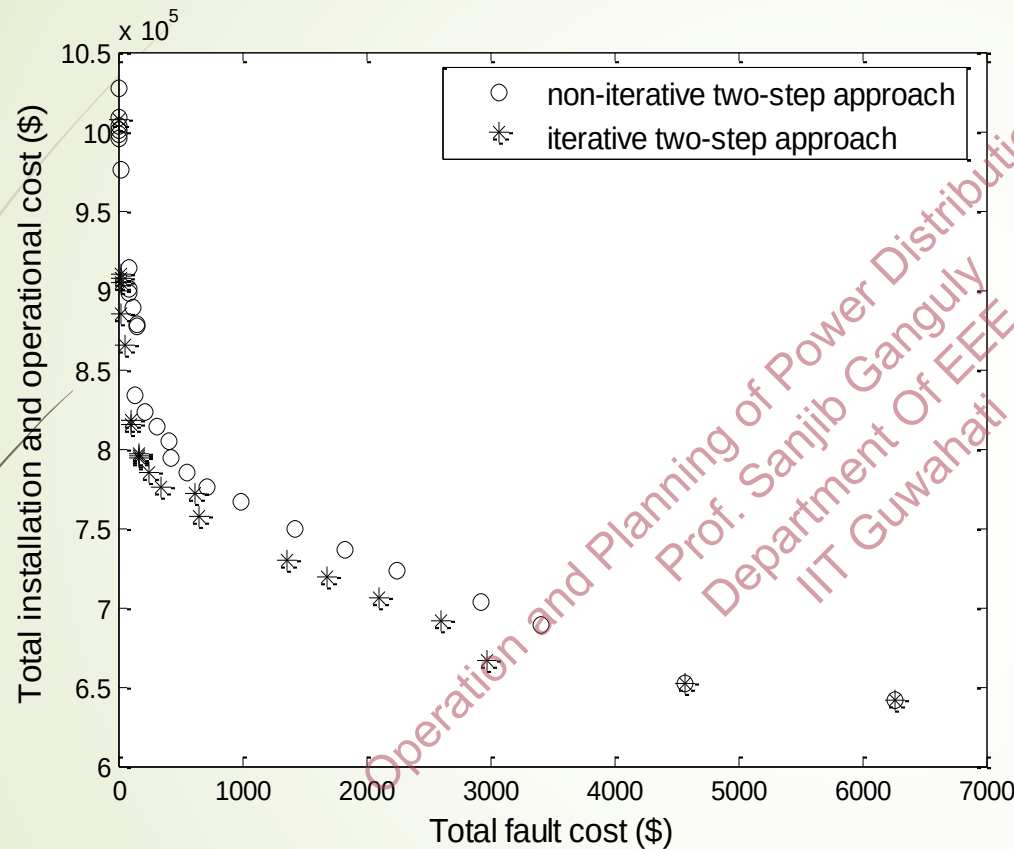


Pareto-fronts for the 54-node system for two different number of stages (i.e., $M=3$ and $M=5$)

Number of stages	Computational time
Five	61.3942 min
Two	237.8742 min

Processor: Intel Pentium D
CPU, 3 GHz, 1GB RAM

Performance comparison of non-iterative and iterative two-step approaches

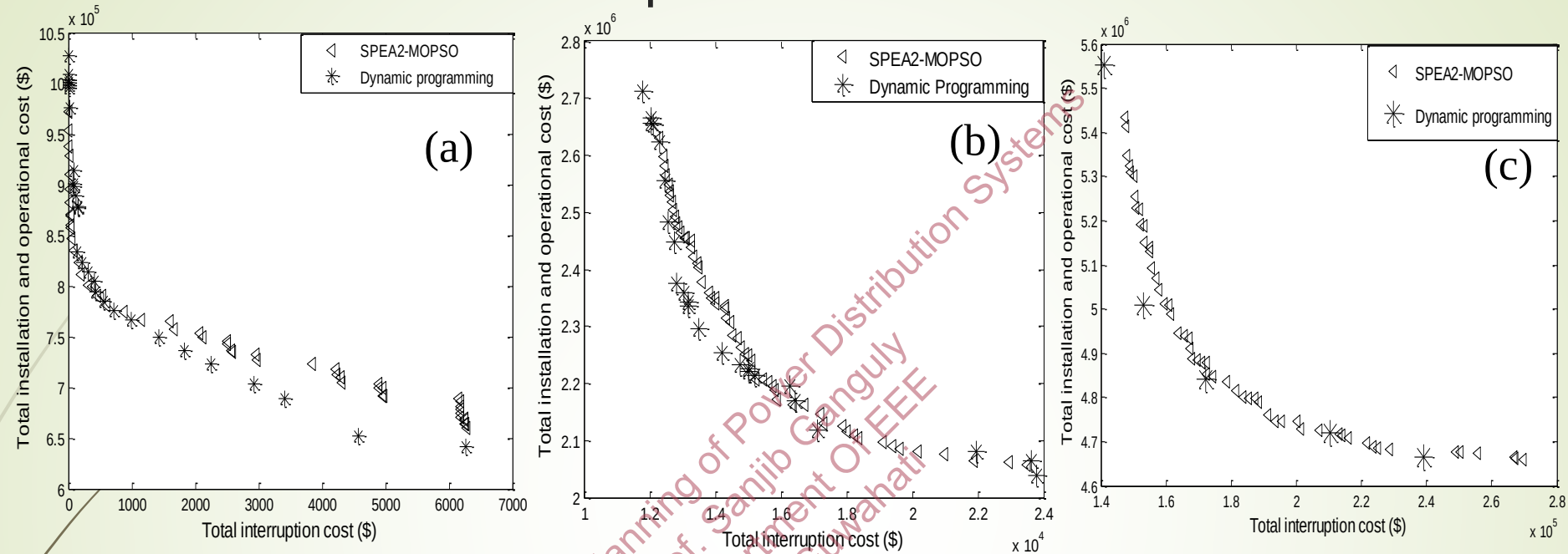


Pareto-fronts obtained with 21-node system

Approaches	Computational time
Non-iterative two-step	1.895 min
Iterative two-step	9.15 min

Processor: Intel Pentium D
CPU, 3 GHz, 1GB RAM

Performance comparison with MOEA



Legends: (a) 21-node system, (b) 54-node system, and (c) 100-node system

Test system	Computation time (min)	
	SPEA2-MOPSO	Dynamic programming
21-node	1.895	1.765
54-node	27.6281	237.8742
100-node	82.8633	892.2187

Performance comparison with MOEA

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Solutions	Objective functions (\$) (MOGA [Carrano <i>et al.</i> 2006])		Objective functions (\$) (Dynamic programming)	
	First	Second	First	Second
Most economical	6.7×10^5	843.79	6.5×10^5	639.6468
Most reliable	17.07×10^5	7.71	14.75×10^5	5.9175

This comparison illustrates:

- ✓ The performance of dynamic programming is better than that of MOEA.
- ✓ The dynamic programming is simpler to implement compared to the MOGA as there is no need for so many heuristic crossover and mutation operators.
- ✓ The dynamic programming suffers from the curse of dimensionality for higher node systems.

Summary

- ❖ Dynamic programming can be used as an efficient solution strategy for multi-objective planning of distribution systems.
- ❖ The curse-of-dimensionality is a major hurdle for the applicability of dynamic programming for more generalized large-scale distribution system planning
- ❖ This becomes a motivating factor for the use of MOPSO in all subsequent investigations.

Multi-objective planning incorporating sectionalizing switches and tie-lines using a new reliability indicator

Objectives:

- ❑ Formulation of a new reliability index, named as **Contingency-Load-Loss Index (CLLI)**
- ❑ To incorporate placement of sectionalizing switches and tie-lines into the planning
- ❑ To optimize number of feeders, feeder routes, number and location of sectionalizing switches, and tie-lines via multi-objective optimization.

Motivations behind new reliability index formulation

- The reliability objective represented by total fault cost is a function of average failure rate and repair durations of each branch of a distribution network.
- Practically, it is very difficult to estimate the failure rates of feeder branches as faults in distribution networks frequently occur due to various unpredictable non-technical reasons, such as short circuit due to contacts of small tree branches, animals etc.
- Repair duration of faults vary with the location and severity of faults.

CLLI

The CLLI is defined as the ratio of average non-delivered load due to failure of all branches, considered one at a time, to the total load.

$$CLLI = \frac{NDL_{avg}}{L_{total}} = \frac{\left(\sum_{i=1}^{N_b} NDL_i \right) / N_b}{L_{total}}$$

where,

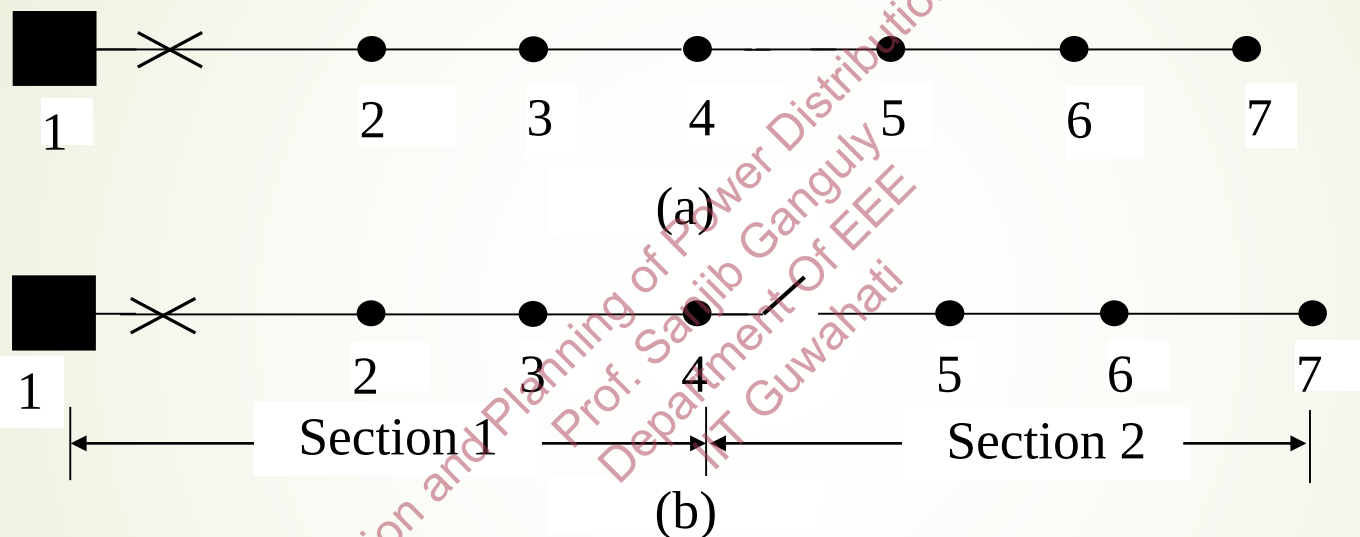
NDL_i non-delivered load due to contingency at branch i

N_b total number of branches in the network

Minimization of the CLLI maximizes reliability of a network

CLLI computation

Let us take an example of two distribution networks with 6 nodes of equal power demand (say, 100 kVA). Substation is at node-1.



A single feeder distribution network (a) without sectionalizing switch and (b) with a sectionalizing switch

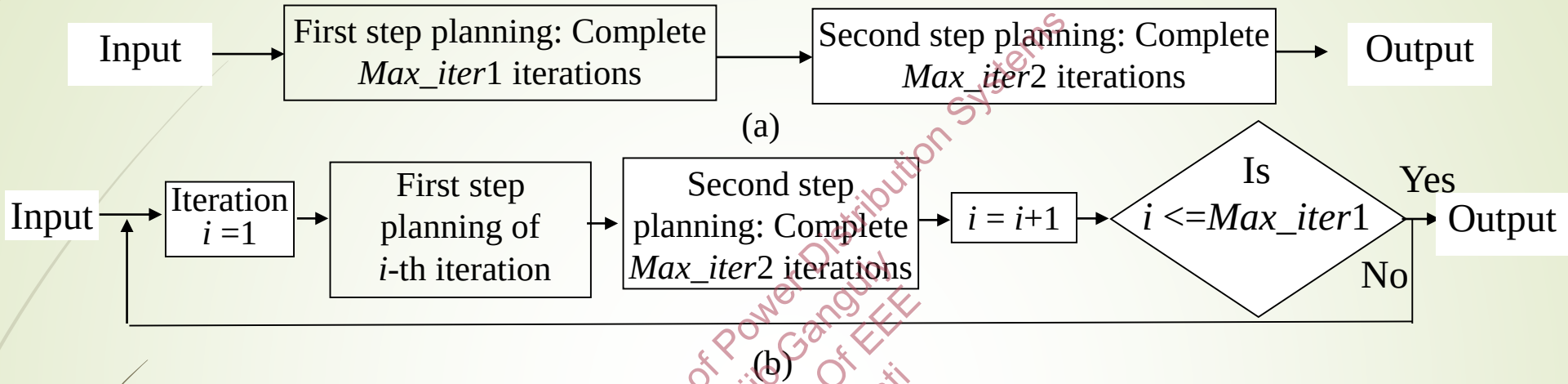
$$CLLI \text{ of Network A} = \frac{(600 \times 6)/6}{600} = 1$$

$$CLLI \text{ of Network B} = \frac{(600 \times 3 + 300 \times 3)/6}{600} = 0.75$$

Multi-objective planning incorporating sectionalizing switches and tie-lines

- This multi-objective planning is done in two steps.
- In first step, network structure with the number and locations of sectionalizing switches is determined.
- In second step, the number and locations of tie-line is optimized for the networks obtained with the first step.
- In an iterative two-stage approach, these two steps are optimized iteratively and its performance is compared with the non-iterative two-step method.
- SPEA2-MOPSO is used as the solution strategy.

Multi-objective planning with sectionalizing switches and tie-lines



Schematics for: (a) non-iterative two-step planning, and (b) iterative two-step planning

Objective functions for first step planning

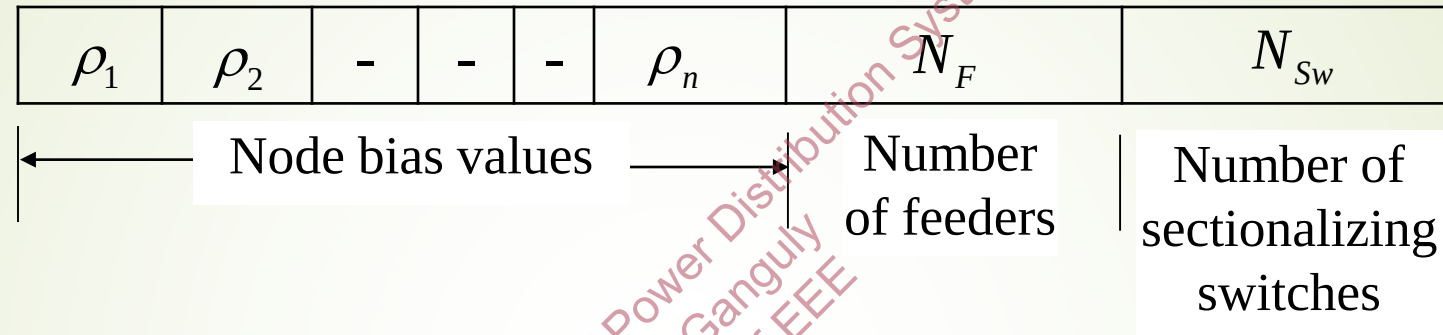
$$C'_{IO} = \sum_{(i,j) \in A_{br}} \left\{ (C_{i,j}^{I_b} l_{i,j}) + (C_{i,j}^{M_b} l_{i,j}) t_a + C^V P_{i,j}^l D_F g t_a \right\} y_{i,j} + \sum_{k=1}^{N_s} C_k^{I_s} + \sum_{m=1}^{N_{Sw}} C_m^{I_{Sw}} + \sum_{k=1}^{N_F} C_k^{I_{bkr}}$$

$$CLLI' = \left\{ \left(\sum_{i=1}^{N_b} NDL'_i \right) / N_b \right\} / L_{total}$$

Objective functions for second step planning

$$C''_{IO} = C'_{IO} + \sum_{j=1}^{N_{Tie}} C_j^{I_T}; \quad CLLI'' = \left\{ \left(\sum_{i=1}^{N_b} NDL''_i \right) / N_b \right\} / L_{total}$$

Particle encoding scheme



(a)



(b)

Proposed particle encoding scheme, (a) first step planning, and (2) second step planning

Pseudocodes for Step-1 optimization

Begin

// η_{pop1} = Size of MOPSO population

// max_iter_1 = Maximum number of iterations

Generate *initial population* for PSO randomly using the proposed *encoding scheme* (both position and velocity);

Decode the *particles* to obtain the networks and calculate the objective functions;

Find the *initial non-dominated solutions* and store them in *elite archive*;

Calculate *fitness of particles* using SPEA2;

$iteration=1$;

While $iteration \leq max_iter_1$

For $i=1, \dots, \eta_{pop1}$

 Update *velocity* and *position* of the particle;

 Decode *particle* to get the number of feeders, feeder routes, and the number and locations of sectionalizing switches;

 Select *conductor sizes* using conductor size selection algorithm;

 Calculate *objective functions* (Eqs. 4.3-4.4) and assign *particle fitness* by SPEA2;

Endfor

 Find out the *non-dominated solutions* and update *elite archive* by SPEA2;

$iteration=iteration+1$;

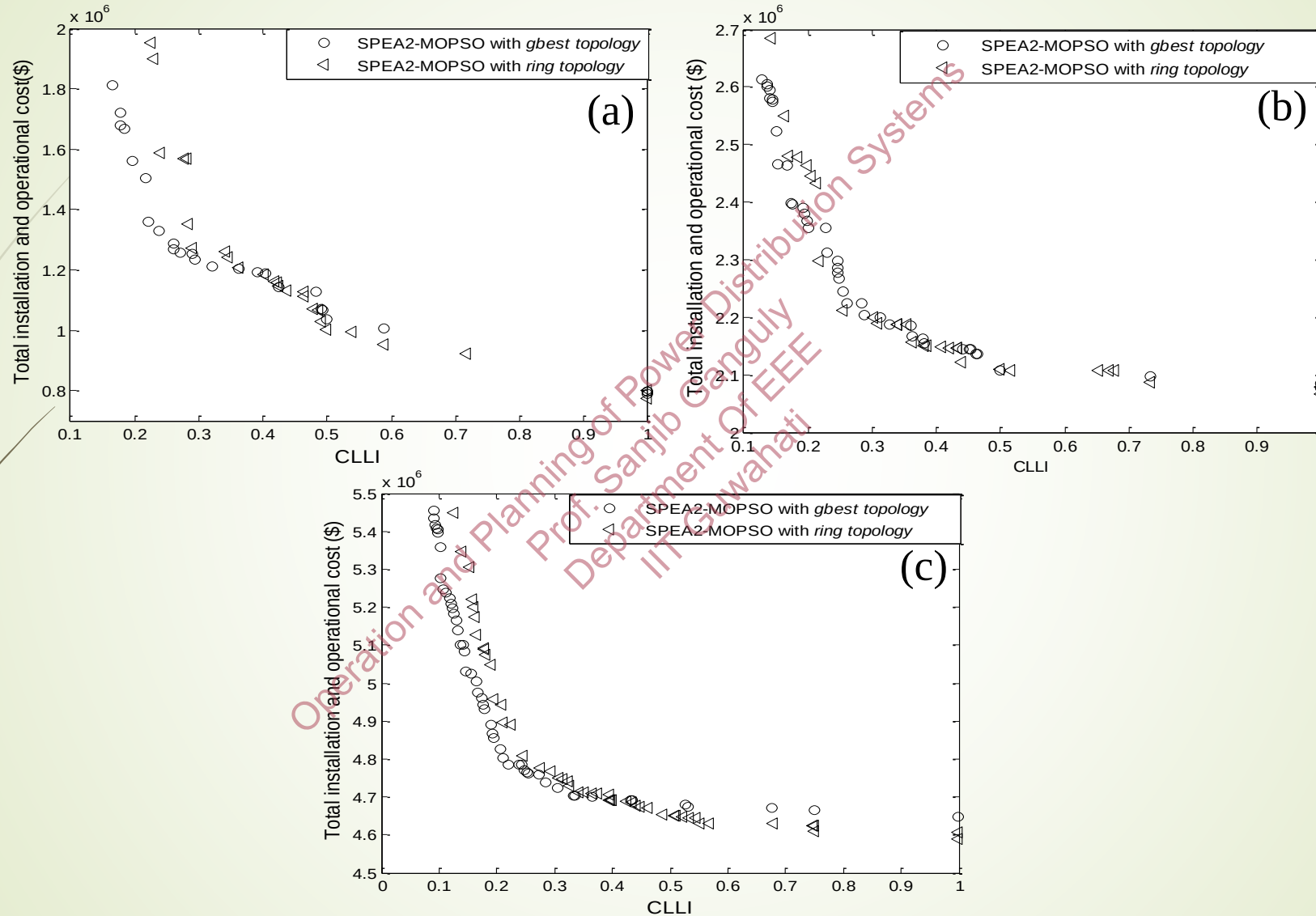
Endwhile

Elite archive contains optimal network structures along with branch conductor-sizes and number and locations of sectionalizing switches;

End

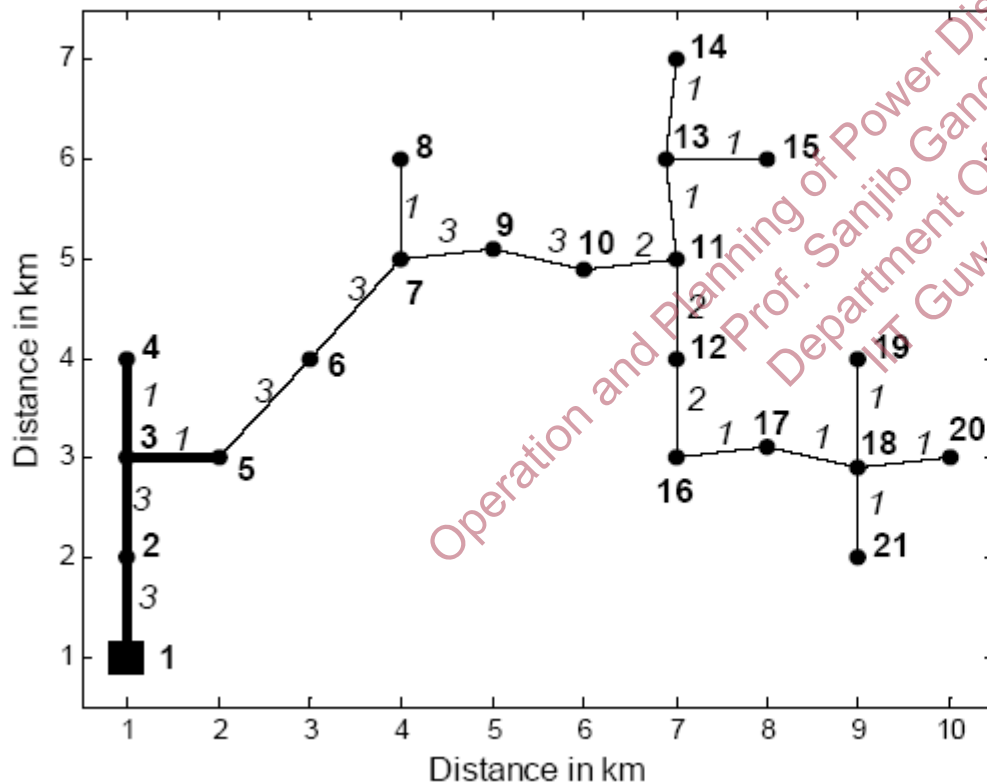
Pareto-approximation fronts

72

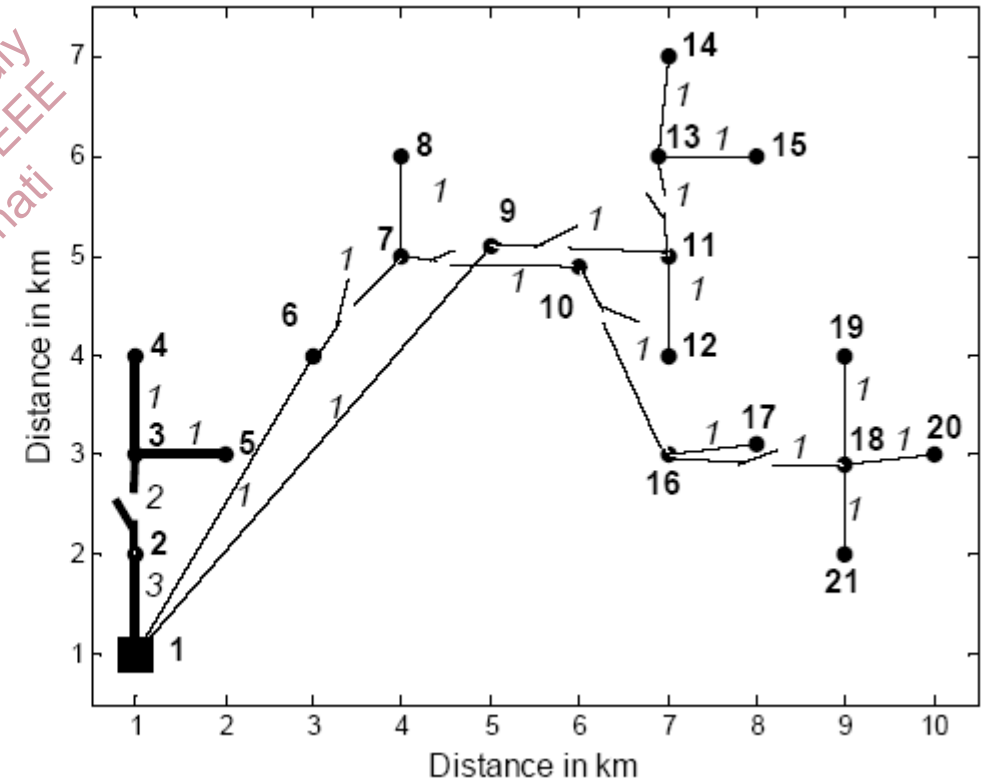


Legend: (a) 21-, (b) 54-, and (c) 100-node systems

Optimization of tie-lines: Solutions of the 21-node system

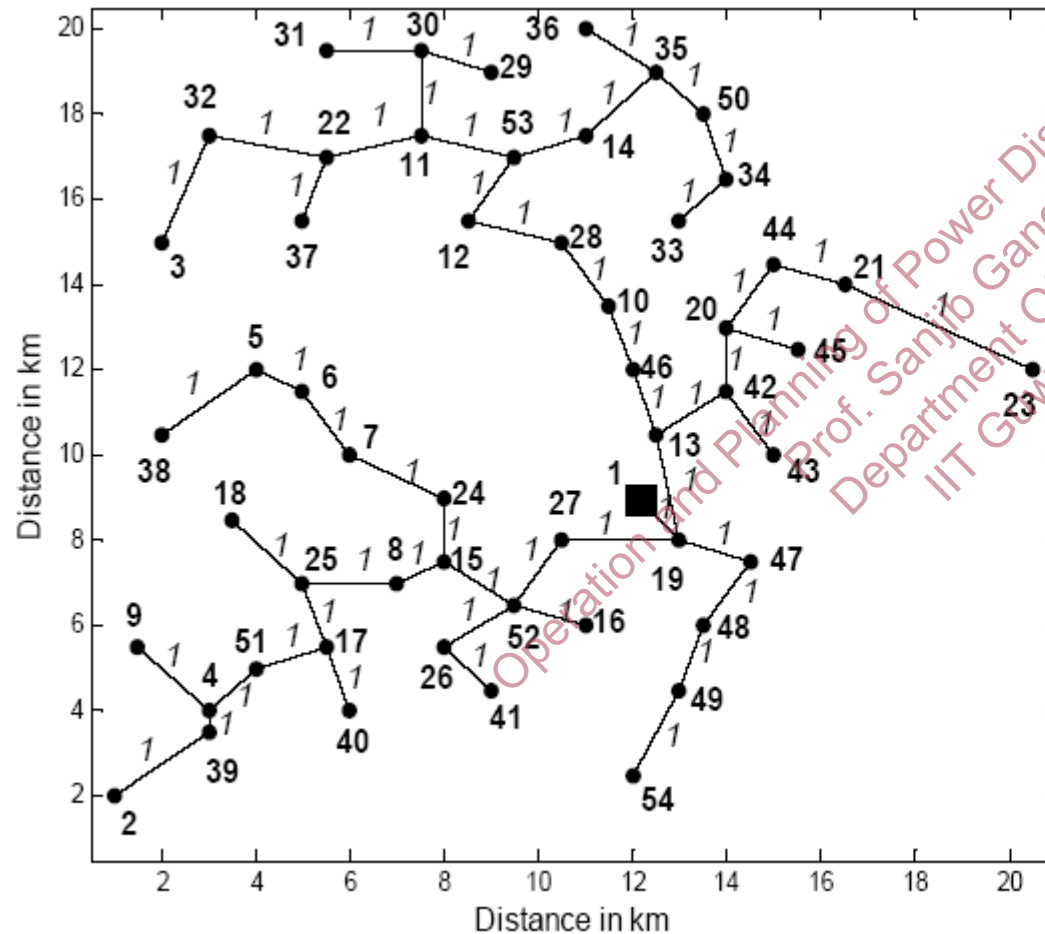


Most economical network

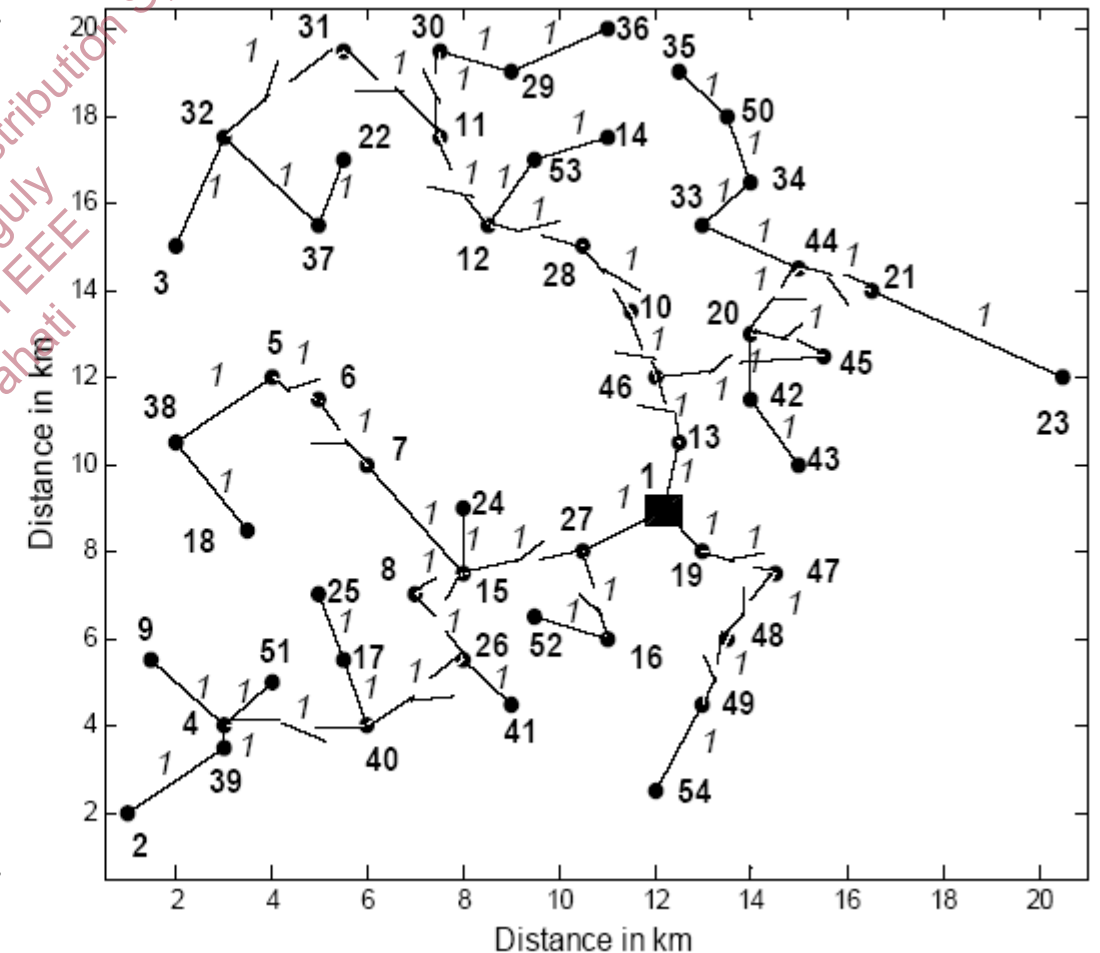


Most reliable network

Optimization of tie-lines: Solutions of the 54-node system

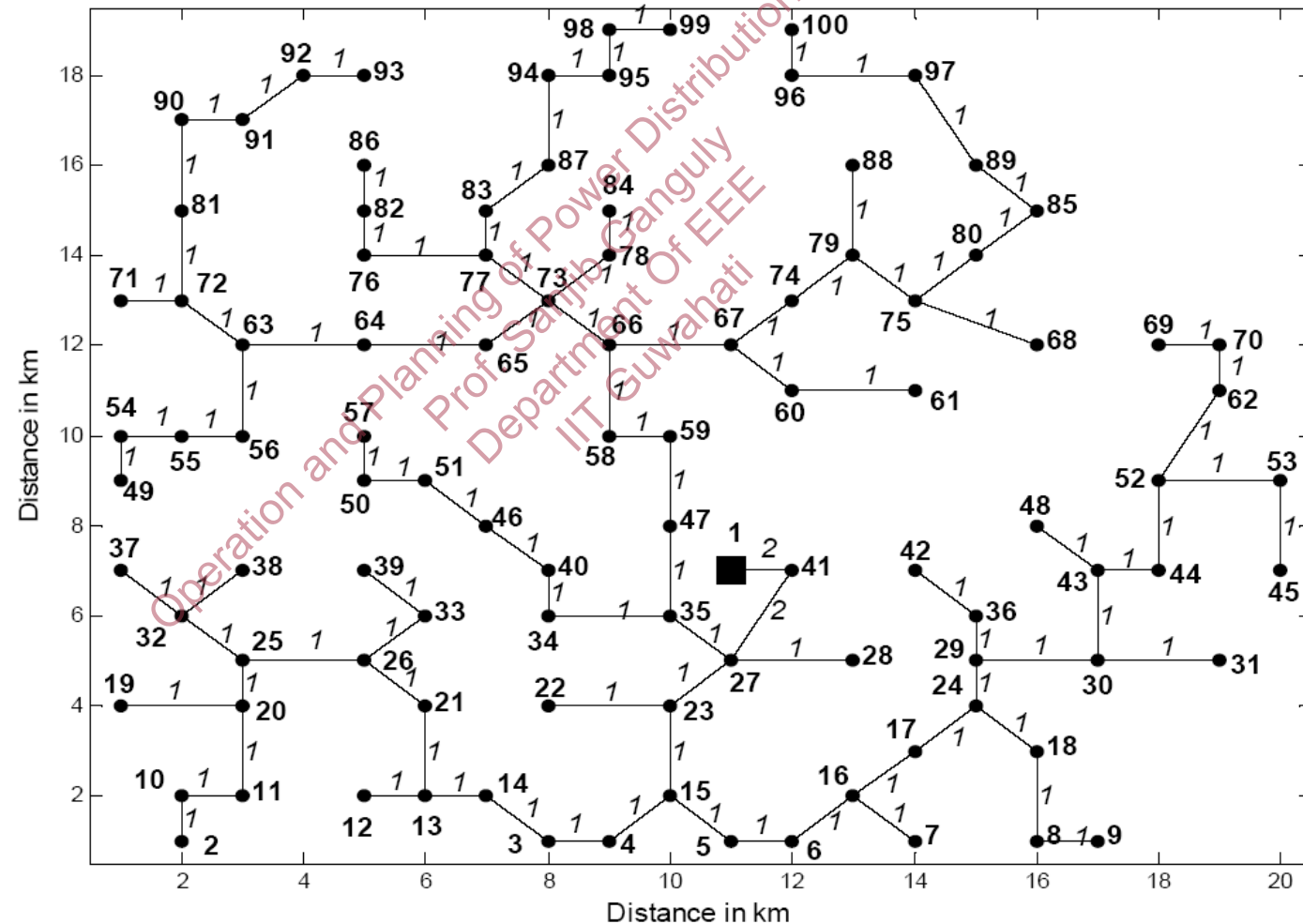


Most economical network



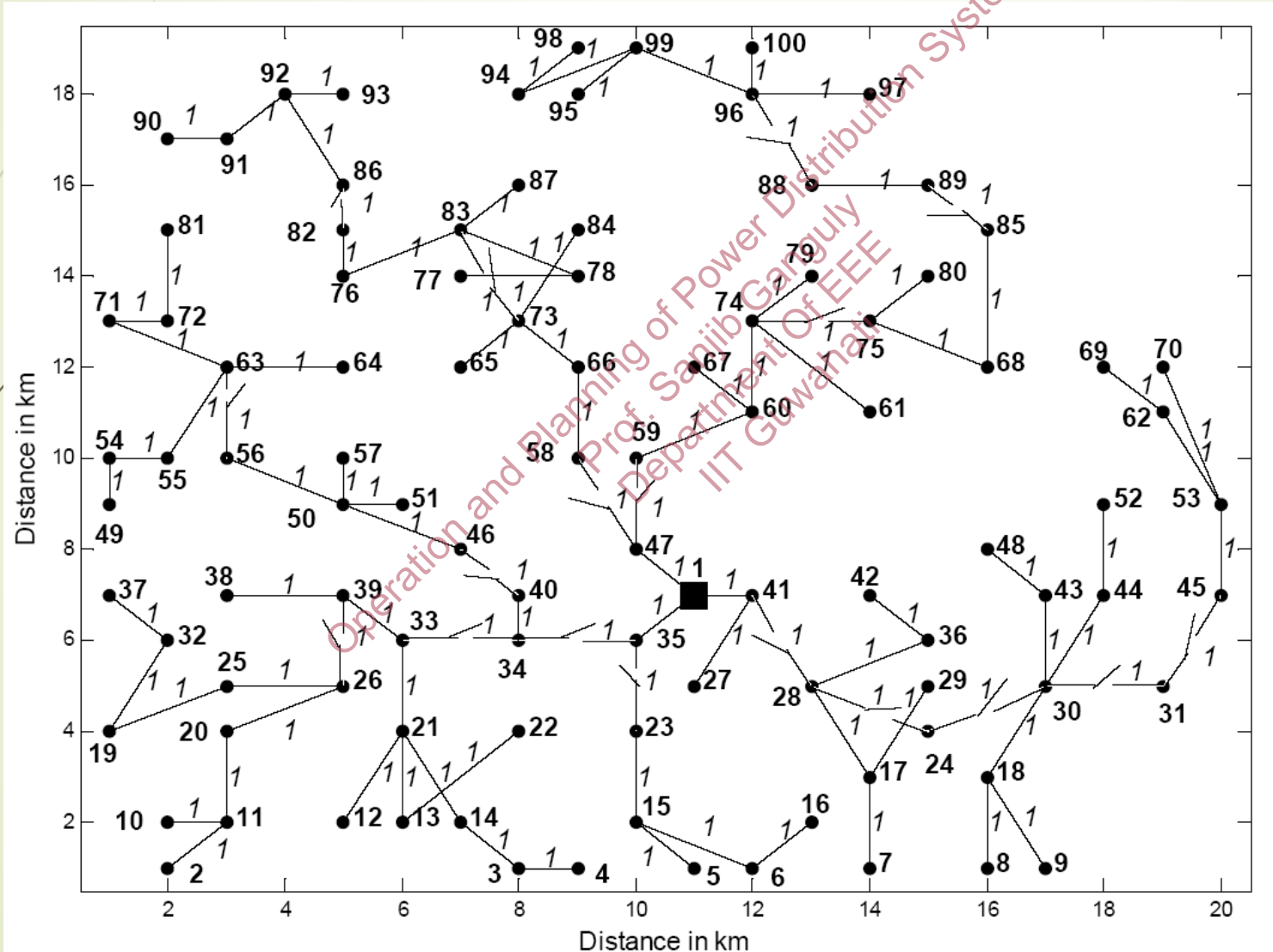
Most reliable network

Optimization of tie-lines: Solutions of the 100-node system



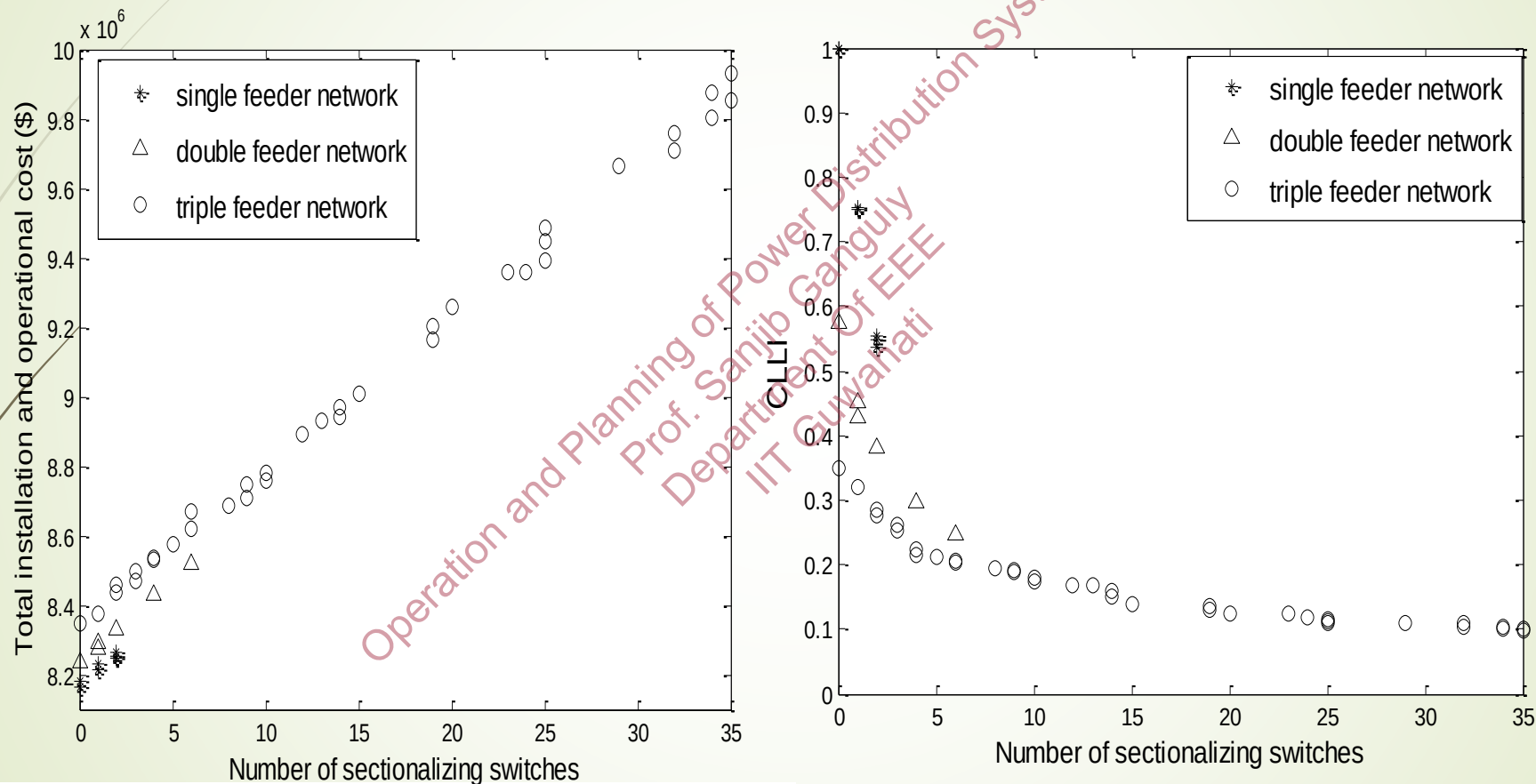
Most economical network

Optimization of tie-lines: Solutions of the 100-node system



Most reliable network

Variations of total installation and operational cost and CLLI with number of sectionalizing switches and number of feeders



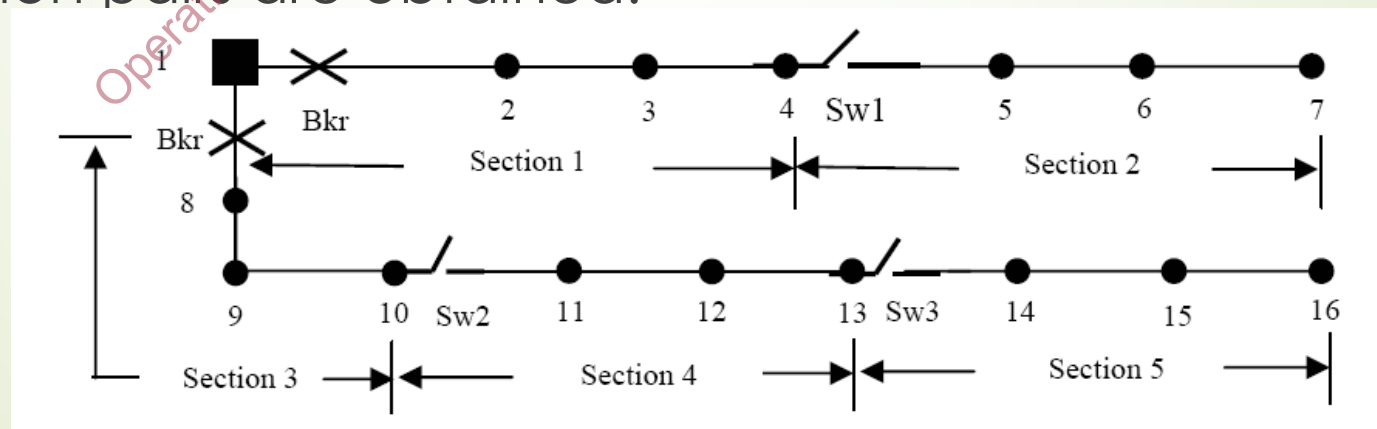
Results of the 100-node system

Optimization of tie-lines: Identification of candidate tie-lines

- Identify all pairs of non-adjacent feeder sections.
- From each non-adjacent pair of feeder section, find out node pair that has the shortest (geographical) distance between the sections; these are considered as candidate tie-line locations between the corresponding feeder sections.
- If there are too many candidate tie-lines, some of the longer tie-lines are discarded depending on chosen maximum number of allowable tie-lines for a network.

Optimization of tie-lines: Identification of candidate tie-lines

- To illustrate this technique, a 16-node distribution network with one substation at node 1 and three sectionalizing switches is chosen. There are five sections in the network. The
- pairs of non-adjacent sections of this network are sections pairs 1-3, 1-4, 1-5, 2-3, 2-4, 2-5, and 3-5. The candidate tie-line between the non-adjacent section pair 1-3 is obtained by calculating the shortest distance between sections 1 and 3. In this way, the candidate tie-lines between all nonadjacent section pairs are obtained.



Optimization of tie-lines

- The optimization of locations of tie-lines is carried out using SPEA2-MOPSO with binary PSO (BPSO) position updating scheme.
- The main concept behind BPSO is the same as that of its continuous version. It is basically another variant of PSO to determine the optimal values of binary variables.
- The velocity updating scheme follows the same expression as that of the continuous PSO.
- However, the position updating is done by a logical transformation of velocity information using sigmoid function (sig).

Optimization of tie-lines: Encoding/decoding scheme

- The particle encoding for tie-line optimization is a simple binary encoding scheme, i.e., 1 (tie-line selected) or 0 (tie-line not selected). Each candidate tie-line is considered as a dimension of the SPEA2-MOPSO particle.

Tie-line 1	-	-	-	Tie-line m
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Optimization of tie-lines: Pseudocodes

Begin

// n_{pop2} = Size of MOPSO population

// max_iter_2 = Maximum number of iterations

Generate *initial population* for tie-line locations randomly (both position and velocity) for the networks representing non-dominated solutions obtained from the first step of planning optimization;

Decode the *particles* and calculate the objective functions;

Find out initial *non-dominated solutions* from the non-dominated solutions of planning Step-1 and initial population of Step-2 and store them in *elite archive*;

Assign *fitness of particles* using SPEA2;

$iteration = 1$;

While $iteration \leq max_iter_2$

For $i = 1, \dots, n_{pop2}$

 Update *velocity* and *position* of the particle according to binary PSO;

 Decode *particle* to get locations of tie-lines;

 Calculate *objective functions* using Eqs. (4.5-4.6) and assign *particle fitness* by SPEA2;

Endfor

 Find out *non-dominated solutions* and update *elite archive* by SPEA2;

$iteration = iteration + 1$;

Endwhile

Elite archive contains optimal network structures that have optimal tie-line locations along with number of feeders, their routes, conductor sizes, switch locations;

End

Summary

- ❖ A novel reliability index (CLLI) is formulated and is used for the multi-objective planning of electrical distribution systems incorporating sectionalizing switches and tie-lines.
- ❖ The CLLI can distinguish the reliability levels of different network structures, for example, single and multi-feeder networks, networks with different number of sectionalizing switches and tie-lines.
- ❖ It does not require the information of failure rates and durations to compute the reliability objective for this planning.

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Thank you

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