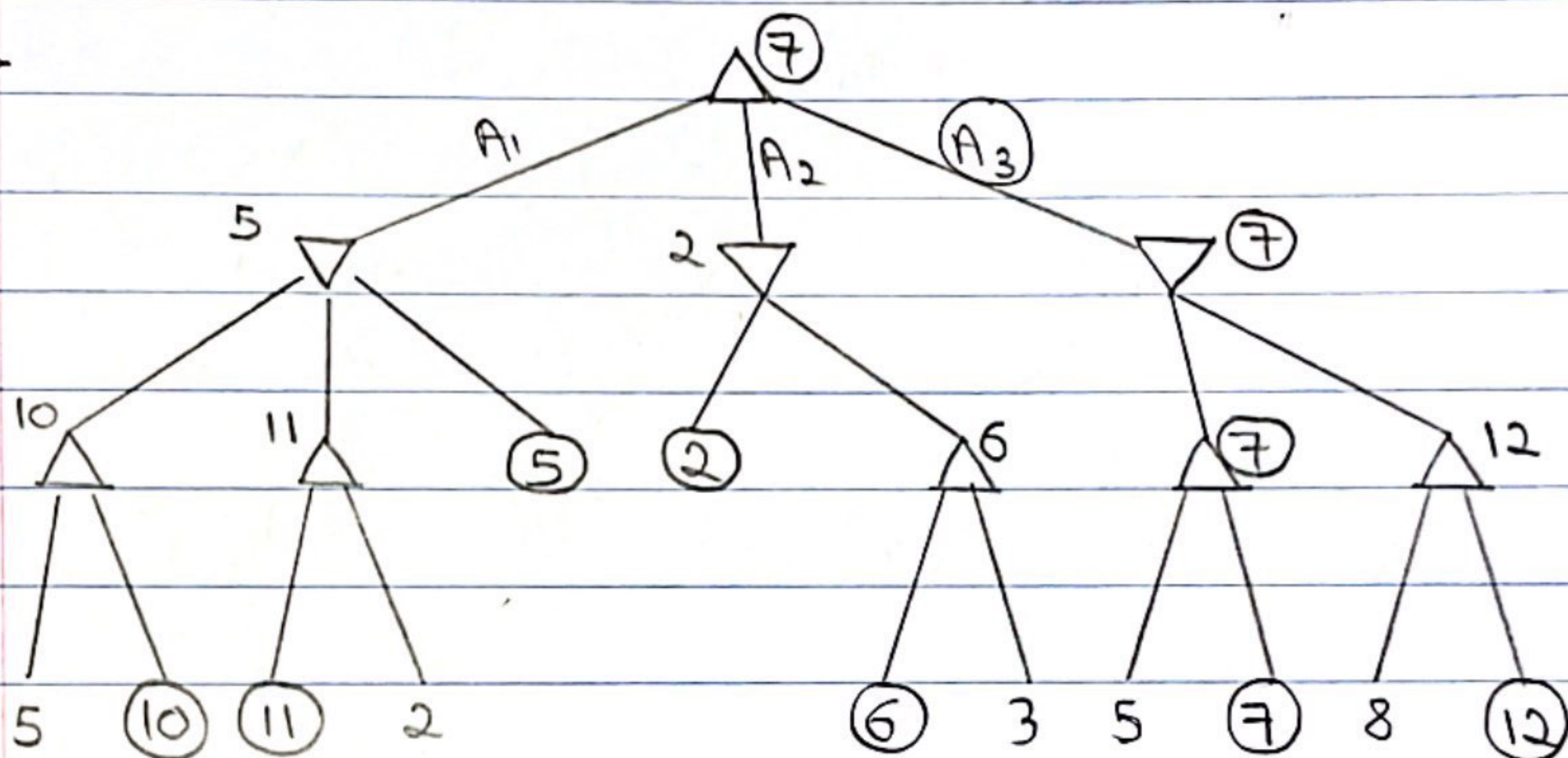


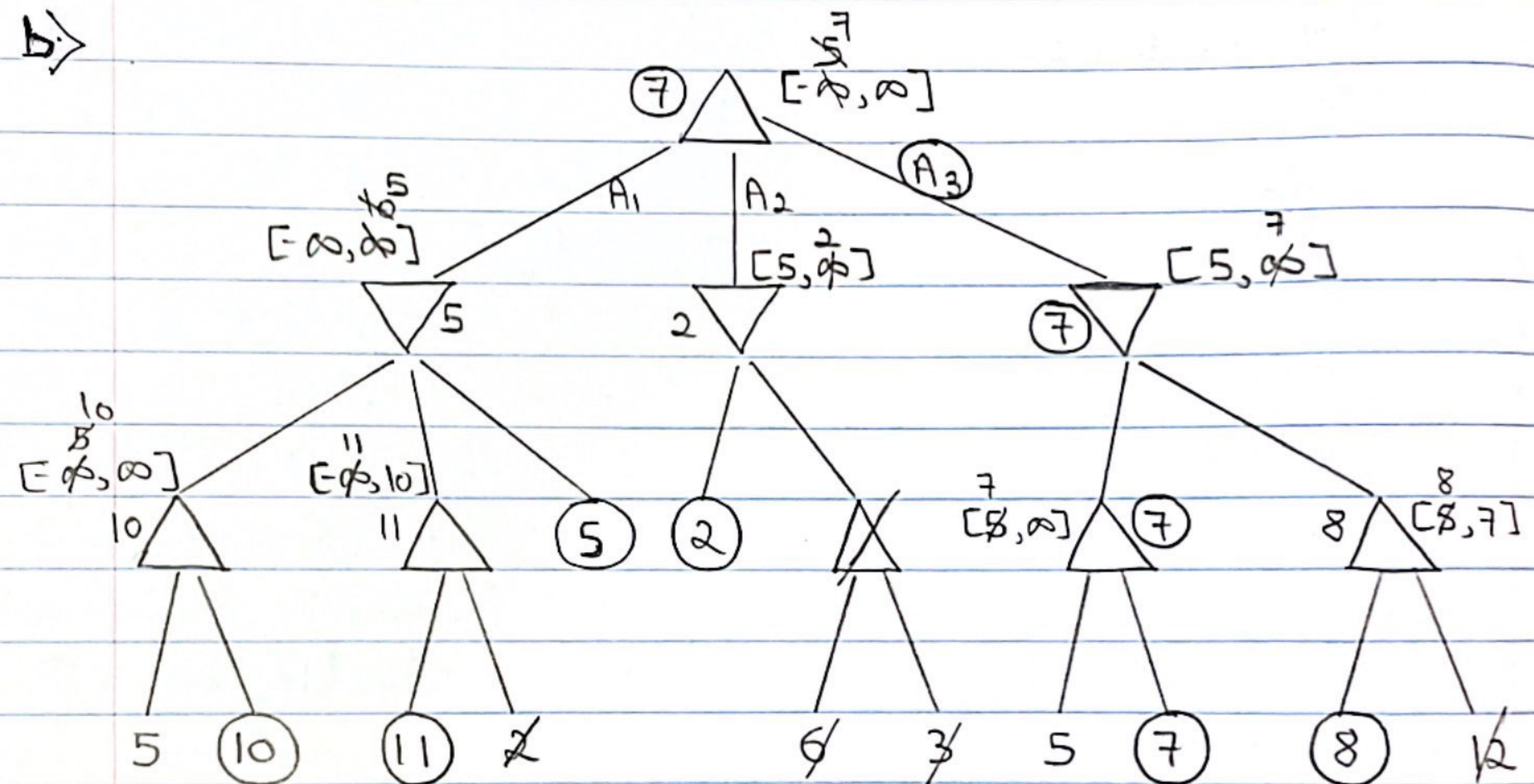
- Assignment 2 -* Task 1 :

a)



From the figure, the action A₃ maximizes the min values to 7. So, we can say that Minimax algorithm will pick action A₃ to execute.

b)



From the figure, Minimax algorithm will pick action A_3 to execute.

Yes, the answer is same as part a.

c) For MIN node:

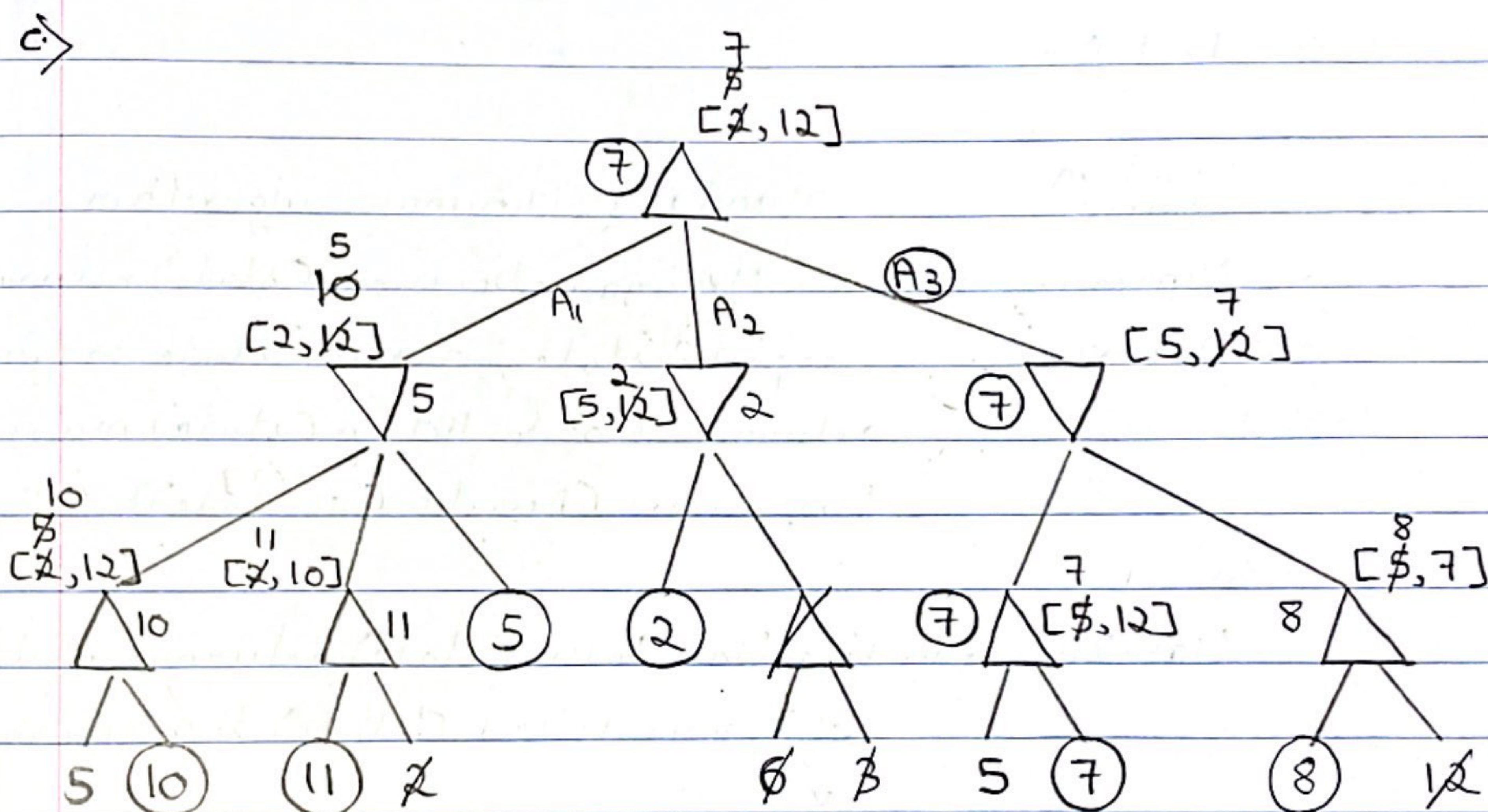
if $v \leq \alpha$ or $v == 2$ then prune

if $v < \beta$ then $\beta = v$

For MAX node:

if $v \geq \beta$ or $v == 12$ then prune

if $v > \alpha$ then $\alpha = v$



If we know that maximum possible value can be 12 and minimum possible value is 2 then we can assign the α & β values accordingly.

$\alpha = 2 \rightarrow$ Highest possible score till now.

$\beta = 12 \rightarrow$ Least possible score till now.

Also, the α - β pruning minimax algorithm can be improved as follows to prune the node if any successor of max node has value = 12 or any successor of min node has value = 2.

* Task 2 -

Function Name	Standard Minimax algorithm
Minimax-Decision	<p>function Minimax-Decision (state) returns an action</p> <p>input: state, current state in game</p> <p>return the a in Action (state) maximizing Min-value (Result (a, state))</p>
Max-Value	<p>function Max-Value (state) returns a utility value</p> <p>if Terminal-Test (state) then return Utility (state)</p> <p>$v \leftarrow -\infty$</p> <p>for a, s in Successor (state)</p> <p>do $v \leftarrow \text{Max} (v, \text{Min-value} (s))$</p> <p>return v.</p>
Min-Value	<p>function Min-Value (state) returns a utility value</p> <p>if Terminal-Test (state) then return Utility (state)</p> <p>$v \leftarrow \infty$</p> <p>for a, s in Successor (state)</p> <p>do $v \leftarrow \text{Min} (v, \text{Max-value} (s))$</p> <p>return v.</p>

Function name	Modified Minimax Algorithm
Minimax-Decision	<p>function Minimax-Decision (state) returns an action</p> <p>inputs: state, current state in game</p> <p>returns the a in Actions (state) maximizing Min-Value (Result (a, state))</p>
Max-Value	<p>function Max-Value (state) returns a utility value</p> <p>if Terminal-Test (state) then return Utility (state)</p> <p>$v \leftarrow -\infty$</p> <p>for s in Successor (state)</p> <p>do $v \leftarrow \text{Max} (v, \text{Min-Value} (s))$</p> <p>return v.</p>
Min-Value	<p>function Min-Value (state) returns a utility value</p> <p>if Terminal-Test (state) then return Utility (state)</p> <p>$v \leftarrow \text{Max-Value} (\text{DeepGreenMove} (state))$ (state)</p> <p>return v.</p>
DeepGreen Move	<p>function DeepGreenMove (state)</p> <p>returns state from min players move</p> <p># do something to return state after</p> <p># min players move without using</p> <p># minimax algorithm.</p> <p>return state.</p>

Here, the only required change is in the Min-Value function.

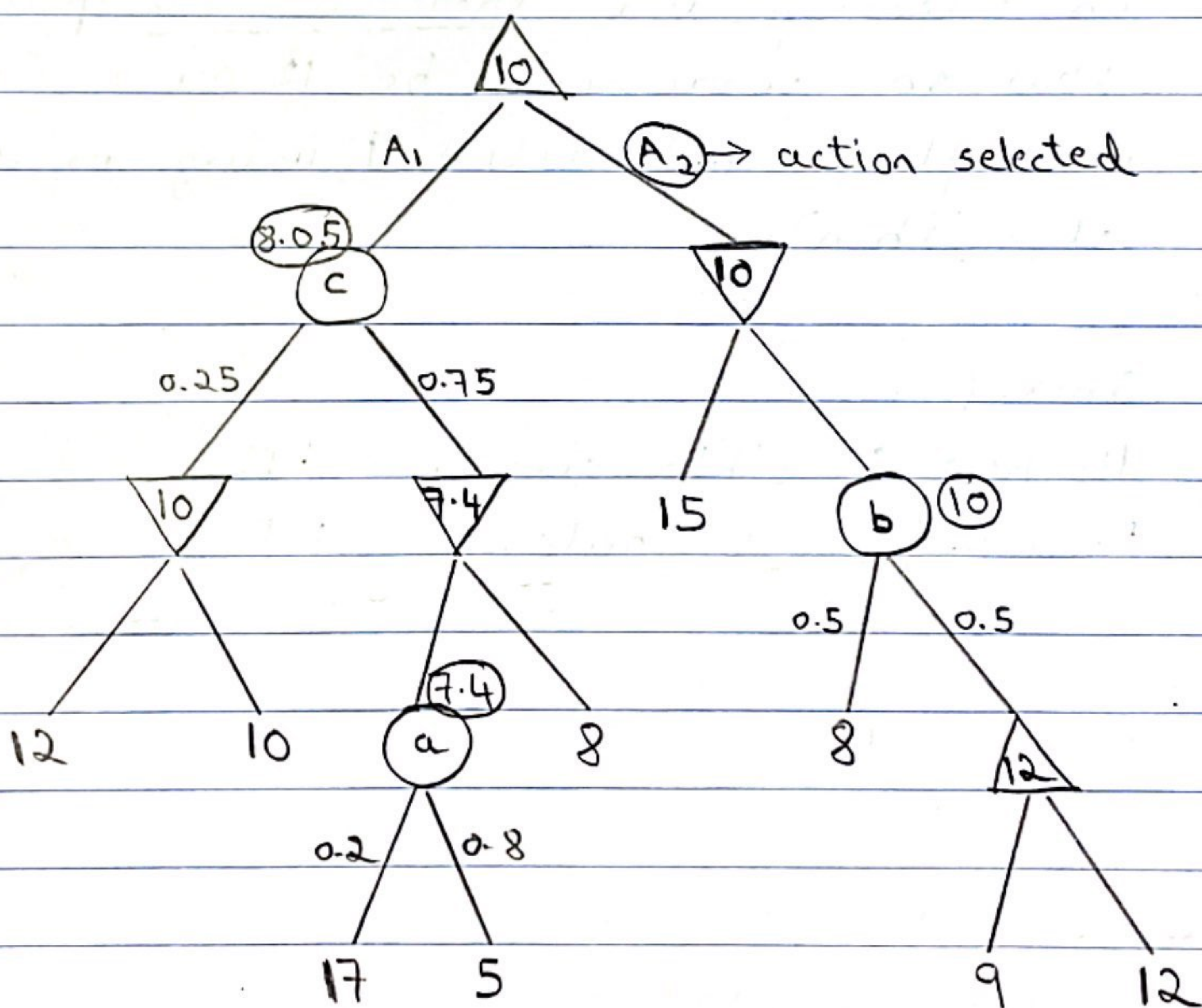
As given in the question, the function DeepGreenMove returns the state after the Min player plays. So now we can use this function in the Min-Value function to predict the Min player's moves and prune the rest of the unnecessary branches in the tree instead of iterating through every possible move that the Min player can play. This can reduce the number of nodes in the tree to almost half.

* Advantage of modified Minimax Algorithm using DeepGreenMove function.

As mentioned above this will result in fewer branches i.e. pruning the branches corresponding to the moves that the Min player will never play and reducing the tree size to approx. half. For an optimal player this algorithm will return the same action as the standard Minimax algorithm using less memory. And for non-optimal player

this algorithm will gives the best action resulting in a state with maximum utility value.

* Task 3:



For node a, value = $(17)(0.2) + (5)(0.8) = 7.4$

For node b, value = $(8)(0.5) + (12)(0.5) = 10$

For node c, value = $(10)(0.25) + (7.4)(0.75) = 8.05$

The action selected by the minimax algorithm is A_2 as it maximizes the minimum values.

After selecting action A_2 , an optimal opponent will select the move corresponding to node b. On selecting that there is 0.5 probability that the score will be 12 or 8 (since the max player will select 8 using minimax algorithm).

Therefore,

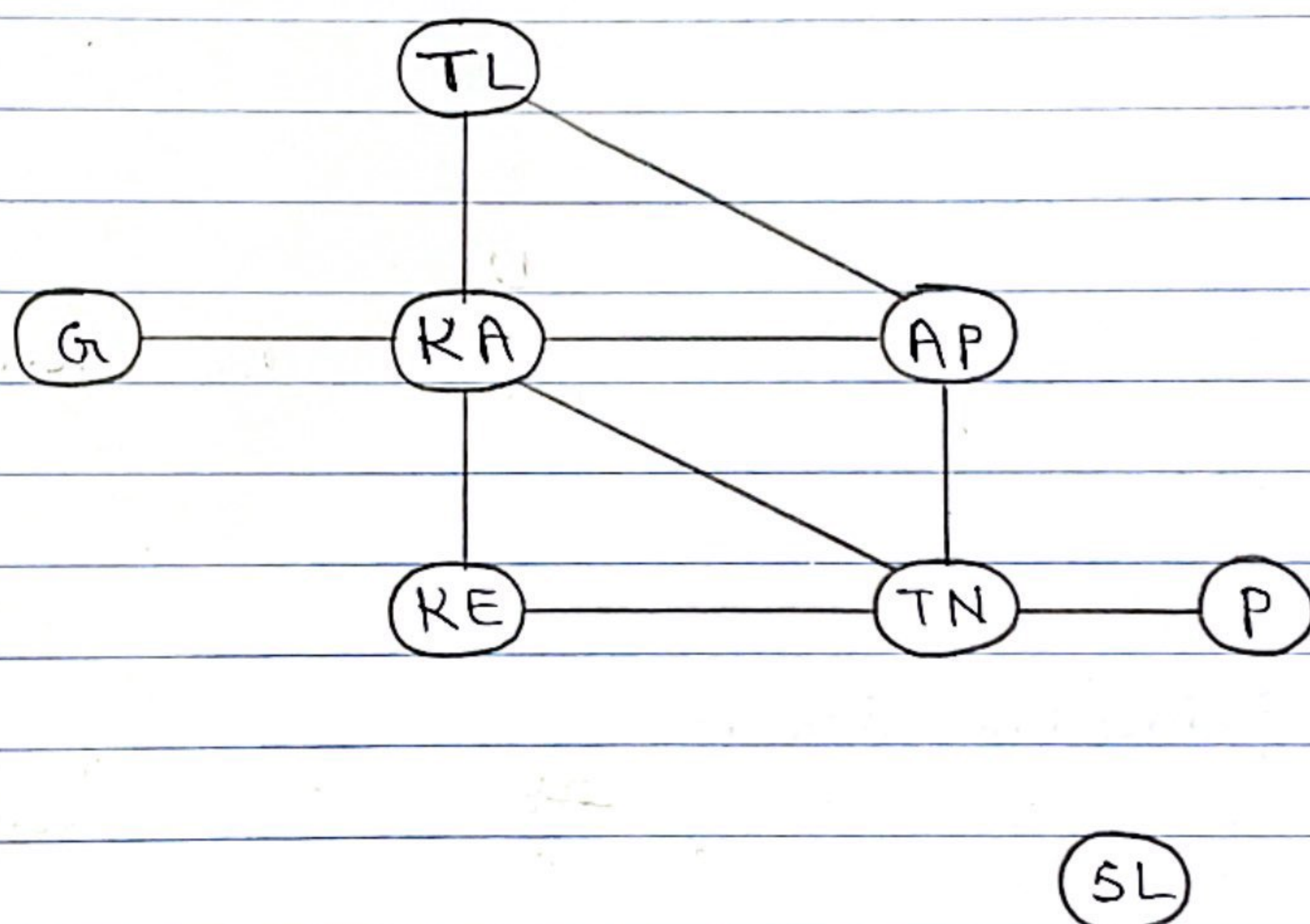
Highest possible outcome : 12

Lowest possible outcome : 8

* Task 4-

a)

Constraint graph -

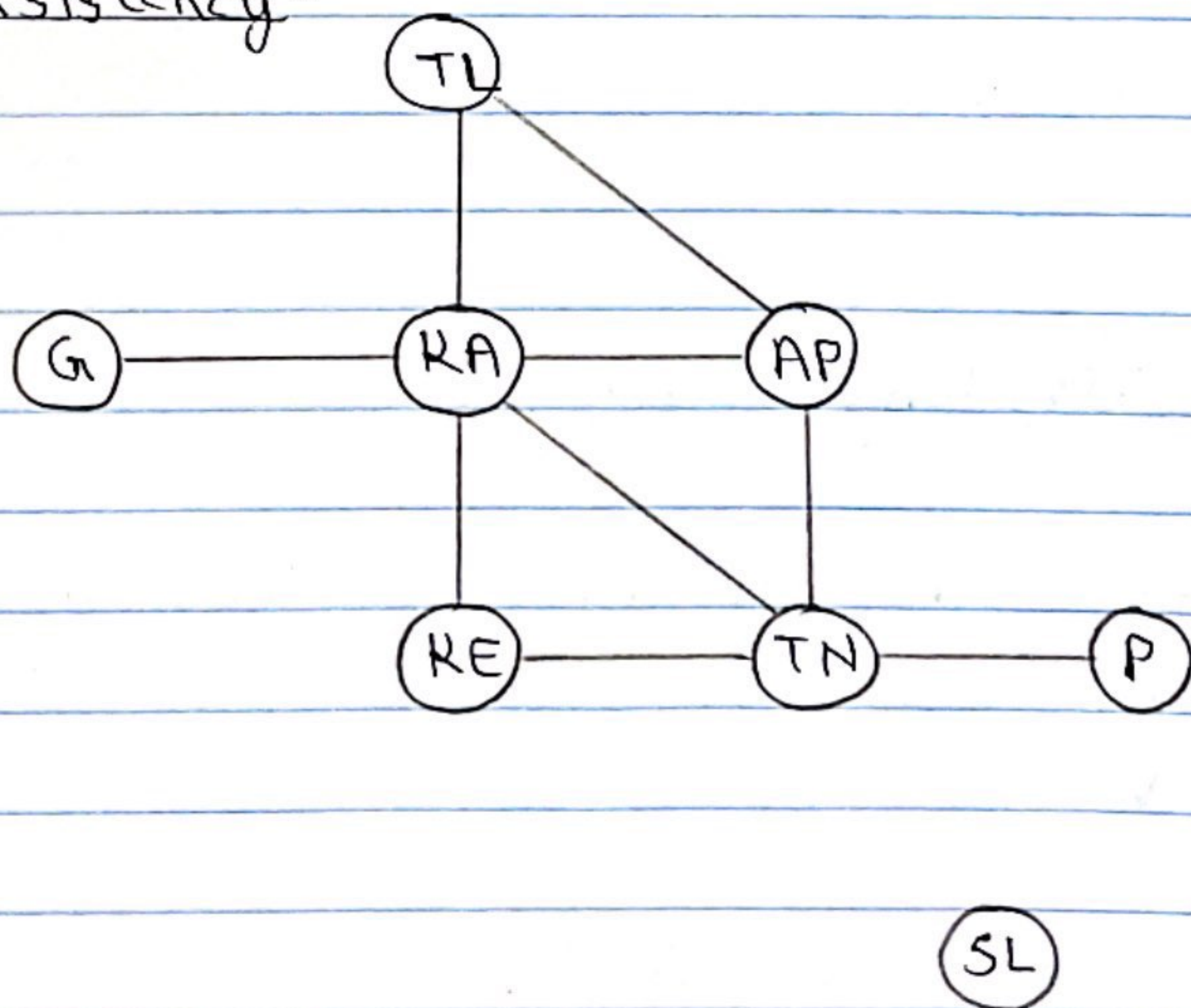


b) Backtracking Search -

Node	KA	TN	AP	KE	TL	G	P	SL
Degree	5	43	321	210	210	10	10	0
MRV	3	32	321	321	321	32	32	3

Level	MRV	Degree Values	Node/Variable Selected
1	3	5	KA
2	2	3	TN
3	1	1	AP
4	1	0	KE
5	1	0	TL
6	2	0	G
7	2	0	P
8	3	0	SL

c) Arc Consistency -



Assigning 'Red' to first variable i.e. 'KA'.

KA TN AP RE TL G P SL

R RGB RGB RGB RGB RGB RGB RGB

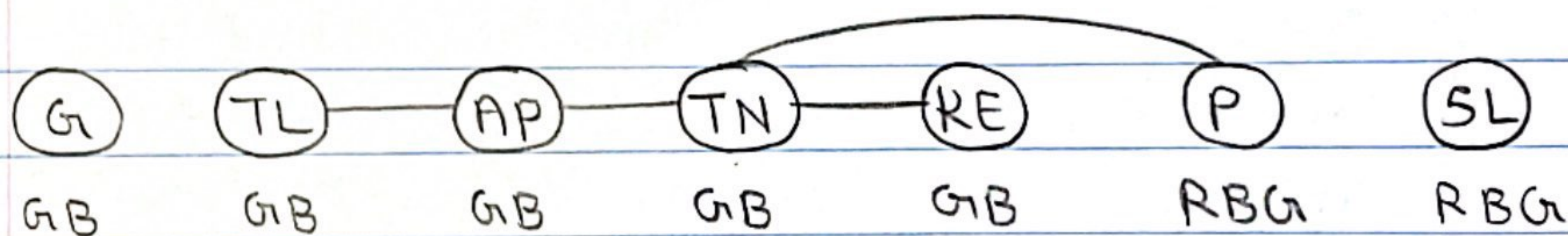
1 G → KA	2 KA → G	5 KA → RE
TL → KA	3 KA → TL	TN → RE
AP → KA	AP → TL	6 AP → TN
RE → KA	4 TL → AP	KA → TN
TN → KA	KA → AP	RE → TN
	TN → AP	P → TN

d) Yes, we can use the structure of the problem to make solving it more efficient.

There are 2 possible ways to do so:

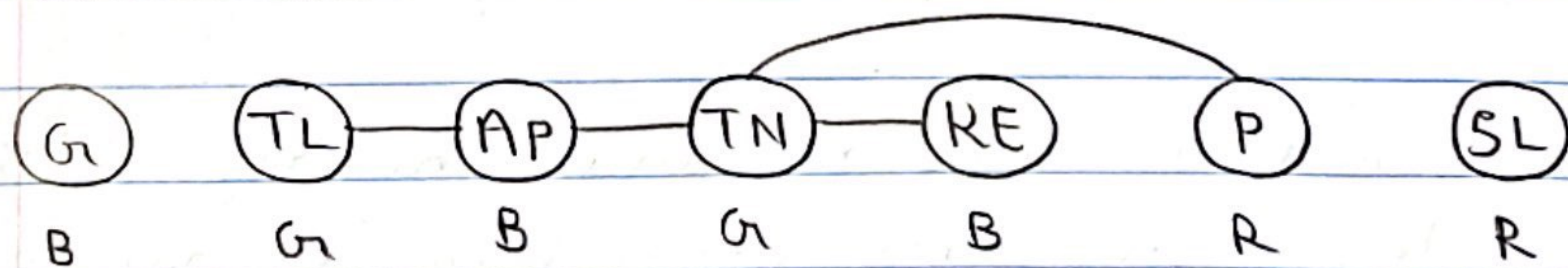
I. First, we can see that the region 'SL' is having no arcs connecting to any other regions. So, we can separate it from the main region and consider to any other subproblem and solve both the problems separately and concatenate the final result.

II. We can see that the region/graph is not cyclic and cannot be solved considering it as a tree (which would be efficient). But we can see that it is nearly tree and we can determine the cut-set here consist of node 'KA' and assigning it to 'Red'. And then solve these subproblem using trees as shown below.



The above sub-problem can be easily solved in $O(nd^2)$ time.

e) One valid Solution -



Assign Blue to G

Assign Red to SL

Assign Green to TL

Assign Blue to AP

Assign Green to TN

Assign Blue to RE

Assign Red to P

Possible Solution:

Red \Rightarrow (KA, P, SL)

Green \Rightarrow (TL, TN)

Blue \Rightarrow (G, AP, RE)