Digital Twin of an Enterprise - A case of the Department of an Academic Institute

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Abstract
An academic institute is a system of systems that consist of departments, administration, and external resources as subsystems. These subsystems can be further divided into smaller active subsystems of students, faculties, external industries, placement unit. For active and dynamic subsystems, predicting its behavior for any action is undeterministic. The complex and uncertain operating environment of an institute makes the decision making process difficult using the regular qualitative analysis based approach. This paper presents a digital twin based approach to enable data-driven quantitative analysis to the decision-making process that can provide feedback to the academic institute on various decision options before taking an actual decision. Our approach has used an artificial intelligence concept called Bayesian Network to develop the digital twin of the department to help department-level stakeholders to take qualitative, data-driven, and simulated verified results that help in taking departmental-level decisions. The Digital twin takes input from the department data, and current situational data, that is fed to the department's Bayesian Network and thus provides feedback to the department regarding various decision options available.

Keywords
Digital Twin, Enterprise Digital Twin, Artificial Intelligence, Bayesian Network, Adaptive Enterprise

1. Introduction

Before the advancement of the Industry 4.0 revolution, Artificial intelligence, and advanced data analytics manufacturing, smart city, healthcare and enterprises sectors were solely dependent on qualitative analytics, quality discussions, high authority people's intuition and field studies to take decisions for attaining goals. However now in this digital era, every sector involves a high level of uncertainty, easy to get influenced by the outside environment and requires smart functioning thus there is a need for every sector to act fast as well as precise in the decision-making process to hold a stand in the market. This section first describes what is Digital Twin and how it being used in various sector. We will discuss some past work on using digital twin in decision making process for enterprises and then we will learn why qualitative approach for decision making is not suited for academic institute and will lay foundation for Bayesian Networks based Digital Twin model for evidence based decision making process.

Digital Twin is a virtual/digital representation of a physical entity with its complete behavior, and operating environment in which both, the physical entity and its digital model is fully

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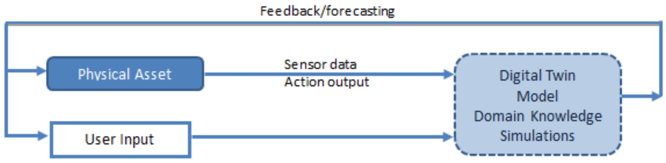

Figure 1: Block diagram of Digital Twin.

integrated in real-time with the bi-directional flow of data, and various actions effect. The digital model continuously takes data/action's effect from the physical entity, user inputs update its domain knowledge adapts to operational changes, performs simulations on the inputs received, and thus provides feedback or forecast to the physical entity. Figure 1 shows the block diagram of Digital Twin that depicts physical entity and digital model connected and communicating data and information to each other. Internet of Things and sensors[1] have provided a large volume of raw data to every sector. This raw data when processed with Artificial Intelligence, data analytics, and data storage[2] facilities, can be made useful for the sectors to gather information and quality insights that can help in data-driven decision-making process. This advancement in technology[3] has paved way for the Digital Twin technology to be widely used in manufacturing, Smart city, Healthcare, and Enterprise sectors. [4]. Digital Twin was first used in the Aerospace industry[4]. In the manufacturing sector, with the technology advancement, real-time data can be sensed and sent from the machines to the digital twin, which then uses data analytic tools to help in the predictive maintenance of machines[5]. Manufacturing processes can also be monitored and using digital twin simulation results processes can be made more reliable, to get maximum production[6]. In the healthcare sector[7], the digital twin concept is paving way for robotic surgery, and patient monitoring. The digital twin of a human being is the fullest use of this concept in the healthcare sector. Cities are known to be a complex eco-system of systems. Few digital twin experiments have been implemented on a city subsystems including transportation[8], and farms[9][10]. A digital twin of city infrastructures like buildings, traffic signals, water lines, and power grids and its simulation results, are useful in visualizing and analyzing in improving livability, and sustainability. One can use the digital twin to monitor and maintain a city's infrastructure. The transportation system is also implementing digital twin technology to avoid accidental hazards, traffic jams, and emergency route/service help.

In recent years, research is done to apply the Digital Twin methodology in the enterprise sector[11]. Paper[12] illustrate how using modeling, simulation and reinforcement learning an enterprise can be made adaptive. Currently, decision-making for an enterprise solely depends on a qualitative approach like discussions among senior organization members and experts' intuitions. No or little quantitative data-driven approach is utilized in making future decisions. Thus, sometimes a decision's outcome is not in favor of the enterprise's goals. Therefore, for the enterprise, one of the major challenges in today's world is to have a decision-making process that is more data-driven, can be rigorously analyzed for various what-if/if-what situations before implementation in actuality, can encompass the uncertainty and dynamic behavior involved in the working environment, and provide some real simulation based feedback to the enterprise. Previously some work on the organisational decision making is done using actor-agent based simulations[13]. This work involves prior knowledge of the behavior of the enterprise and its subsystems for modeling the digital twin.

We have taken academic institute's department as an enterprise for which various decisions are being taken by the administration of the department, stakeholders, and faculty. To understand the department's dynamic behavior, uncertainty, and input-output variables, let us take one example. The department sets a goal to raise funds. For this example, extra funds raised is an output variable. To achieve this goal, the department decides to start a few online executive programs, which can be considered as an input variable for this case. Introducing several online executive programs will raise extra funds however introducing beyond a certain number of online executive programs will affect faculty time management for research work that will in turn impact research quality and research papers submitted by the department. Similarly, it can also affect the department's regular academic courses and thus other qualitative variables associated with academics like department's perception to outside world, placements statistics and student satisfaction. One decision may have positive impact on some goals and can lead to a negative impact on other goals. The above example depicts how various variables are dependent and provide uncertainty.

Thus, it is a need for modern institute to have a data-driven approach for decision-making and before the implementation of a decision what-if/if-what analysis results can be obtained and evaluated. For multiple dependency and uncertainty, the Bayesian Network[14] based model provides probabilistic reasoning for the decision-making process. In this approach, Bayesian Network is created with input-output variables as nodes, dependency among these variables is depicted using a directed acyclic graph, and using past and current data Bayesian Network learns the values of its variables and dependency behavior i.e. positively or negatively dependent. Once the Bayesian Network is created then various what-if/if-what analyses could be done using AI inferences. This is a data-driven approach to the decision-making of an enterprise.

2. Problem Statement

Consider an educational institute's subsystem department that aims to achieve more research paper publications then previous year publications. To achieve this goal institute has to take few decisions. Few such decisions could be like faculty spending more time to research work, more number of research scholar, more number of hours spent by scholars on research work, more international conferences supported by the department, and more high end research equipment. If the institute takes the decision of faculty spending more time on research work then it would directly affect teaching hours of a faculty and will thus hamper the academic area of the institute, and other administration related work of the faculty. Similarly, if the institute decides to have more number of conferences/international travel then it will affect the institute's finances to support other goals, funds for high end equipment and many other quantitative as well as qualitative factors of the institute. The above example again helps to shows how department's defining variables are dependent to each other with high level of uncertainty and have dynamic behavior and working environment[13].

To define the problem statement mathematically, X_1, X_2, X_3, $..X_n$ are n different dependent or independent events/variables of a department. Multiple events occur at the same time and thus affects other events. So, given the department data for these events, a model is needed to learn from this data and create a complete numeric probabilistic reasoning model for the case when all events occurs at the same time. Thus, problem statement for the paper is to develop a mathematical model that can give compute $P(X_1, X_2, ..X_n)$ by self learning from the data provided and subsequently helps in providing feedback for various what-if/if-what analysis to the department. For this Bayesian network based digital twin is being designed and developed which is discussed in the next section.

3. Methodology

In this section, we present a brief about Bayesian Networks. Then we depicts how Department can be modeled using Bayesian Network.

3.1. Bayesian Network

Bayesian Networks[14] represents probabilistic graph based model of an uncertain domain. In this, all the random variables are considered as nodes of the graph. Directed link between two nodes defines dependency among them (Parent-child). Joint probability is a way of calculating the likelihood of all the variables occurring together. Joint probability distribution of Bayesian network is given as,

$$P(X_1, X_2, ..X_n) = \prod_{i=1}^{n} P(X_i|Parent(X_i)) \quad (1)$$

Here X_i represents random variables.

According to the Total Probability rule, if the probability of an event is unknown then using marginalization over all other events in the joint probability distribution one can calculate marginal probability of an event. Mathematically, to calculate $P(X_k)$ total probability law states,

$$P(X_k) = \sum_{i=1, i\neq k}^{n} P(X_1, X_2, ..X_n) \quad (2)$$

Similarly, using joint distribution and total probability law, conditional probability can be calculated as,

$$P(X_k|X_c) = (\frac{1}{P(X_c)}) \sum_{i=1, i\neq k,c}^{n} P(X_1, X_2, ..X_n) \quad (3)$$

Here, $\frac{1}{P(X_c)}$ is a normalization constant.

Thus with full join probability distribution we can infer probability distribution of any variable under any conditional circumstances or no evidences given situation.

Figure 2 is a simple example of a Bayesian network. This Bayesian network depicts event C depends on two independent events A and B.

Joint probability of the figure 2 Bayesian network is given as,

$$P(A, B, C) = P(C|A, B)P(A)P(B) \quad (4)$$

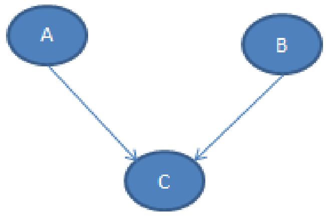

Figure 2: Simple Bayesian Network

To infer probability of event C, equation (2) is used as,

$$P(C) = \sum_{A} \sum_{B} P(A, B, C) \tag{5}$$

Similarly, to infer $P(C|B)$ equation (3) is used as,

$$P(C|B) = \frac{1}{P(B)} \sum_{A} P(A, B, C) \tag{6}$$

3.2. Department as Bayesian Network

So far we have understood that for a domain that involves a high level of uncertainty, and consists of highly interrelated variables the probabilistic reasoning approach serve the best for the decision-making process. Figure 3 depicts a block diagram of the abstract level modeling of the department using the Bayesian Network. In the department model, nodes of the network are input and output variables of the department. For the model to learn, here, synthetic logical data is fed. Once, the model learns from the data we can provide input numerical values to the model via input variables. Input variables of a department are selected after discussion with the department's higher authorities. These variables define or characterize a department. Then the model using joint, total, and conditional probability, technically termed as inferences, provides numerical valued outputs. Thus, by providing different sets of input variables, the model can be utilized for rigorous what-if/if-what scenarios and provides data-driven feedback for each set of input variables. The concerned authority can choose or alter the set of input variables that is most likely to produce output variables helping in achieving the goals.

A department has various quantitative as well as qualitative output variables. For the model, the most interesting and important output variables for the department's growth are chosen. Few important qualitative variables are satisfaction level, and Research Skills that can be used to characterize the department. Using the proposed approach, the qualitative variables can be analyzed numerically. Table 1 contains important department's input variables and table 2 contains important department's output variables.

Using the input and output variables let us understand how Bayesian Network of the department is created. In general, Bayesian networks, for the department's model, are created using the empirical understanding of the department, discussion among higher authorities, and logical dependencies of different variables on an output variable. An output variable of interest can be directly influenced by input variables and other output variables. There are also indirect

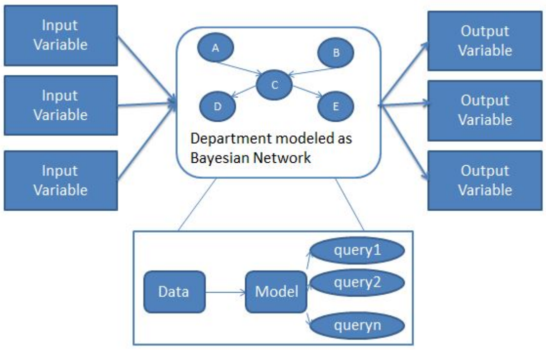

Figure 3: Block diagram of abstract level depicting methodology

Table 1
Department Input variables

No. of Faculty Members	Faculty Member Time
No. of Technical Staff Members	Staff Member Time
No. of Ph.D. Students	Ph.D. students Time
No. of M.Tech. Students	M.Tech. Students Time
Total Research Funding	No. of Research Lab
No. of Research Projects	Consultancy Projects Funding
No. of Executive Degree Programs	No. of Diploma/Certificate Programs
Total funding from executive, Diploma/certificate Programs	Visitors Travel expenses
No. of Visitors	Non-recurring Expenditure
Recurring Expenditure	Non-recurring Expenditure

Table 2
Department Output variables

Student Satisfaction Level	Placement statistics
Student Research Skill	Student Study time
Student Free time	Student Research time
Research Papers per Faculty	Faculty Satisfaction Level
Staff Satisfaction level	Faculty Research Time
Faculty Free time	Faculty Academic Time
No. of support for International Travel of Ph.D. student	
Conferences/Workshops/ Symposiums Organized by the department	

logical dependencies on input variables that influence variable of interest via other output variables. For precise results from the Bayesian Probabilistic approach, instead of creating a whole Bayesian network of the department, this methodology has created Bayesian networks using variables that are closely related/ or affecting each other. In the subsequent networks, rectangle shaped node is an input variable and oval shaped node is an output variable. A short acronym of the variable is mentioned on top of its node.

The figure 4 Bayesian network depicts the output variable Placement statistics and student satisfaction are dependent on inputs like number of faculty members, research labs, etc and other output variables like student's self study hours, student's free time, college support for international conferences, etc. All inputs and outputs have positive impact on the Placement statistics and student satisfaction output. Equation (7) is the Joint Probability of the complete network.

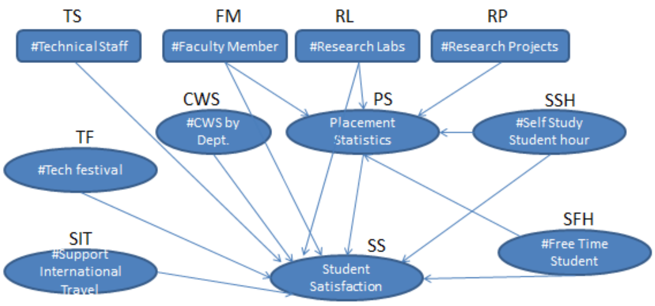

Figure 4: Bayesian Network for Placement Statistics and Student Satisfaction

$$P(JointProbability) = P(SS|SIT, SFH, PS, CWS, TS, FM, TF, RL)*$$
$$P(PS|SSH, RP, RL, FM) * P(SFH) * P(SSH)*$$
$$P(CWS) * P(TF) * P(TS) * P(FM) * P(SIT) * P(RL) * P(RP) \quad (7)$$

The figure 5 Bayesian network depicts how the output variables Research Skills and Research Papers per faculty are dependent on other input variables like number of research labs, research students count, etc and output variables like research hour by student and faculty, number of academic visitors, etc. All inputs and outputs have positive impact on the Research skills and Research Paper output. Equation (8) is the Joint Probability of the complete network.

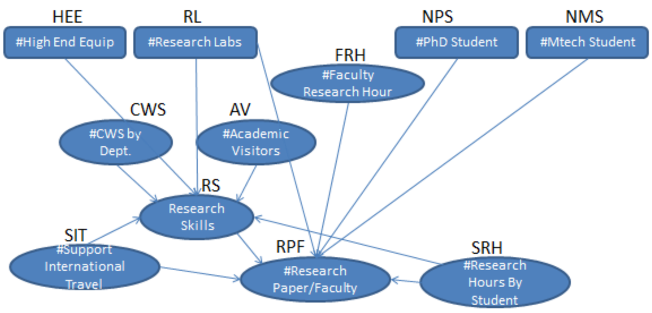

Figure 5: Bayesian Network for Research Skills and Research Papers per faculty

$$P(JointProbability) = P(RPF|SRH, SIT, NMS, NPS, FRH, RL, RS)*$$

$$P(RS|SIT, CWS, AV, RL, SEE, SRH) * P(ST) * P(SRH)*$$
$$P(NMS) * P(NPS) * P(FRH) * P(AV) * P(CWS) * P(RL) * P(HEE) \quad (8)$$

The figure 6 Bayesian network depicts how the output variables Faculty Time and Student Time are dependent on other input and other output variables. Here inputs Diploma program and Executive program have positive impact on Faculty teaching hour and at the same time have negative impact on Faculty Research hour. Similarly, more number of conferences and Academic visitors have negative impact on self study hour but at the same time have positive impact on student research hours. Here, one independent variable affects in a trade-off manner to two different time output. One of the hidden aspect of this approach is that through the learning data, network itself learns positive or negative co-relation between dependent variables. Equation (9) is the joint probability of faculty time management network and (10) is the Joint Probability of the student time management network.

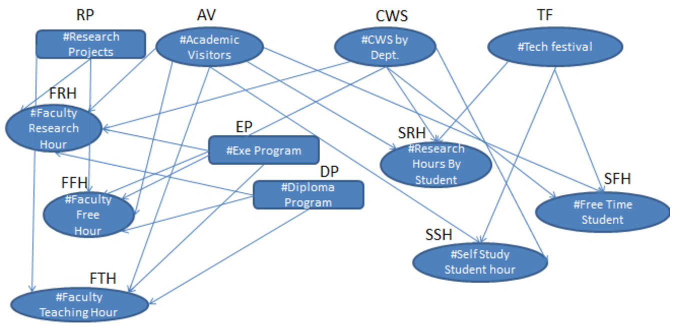

Figure 6: Bayesian Network for Faculty and Student Time management

$$P(JointProbability) = P(FRH|RP, AV, CWS, EP, DP) * P(FFH|RP, AV, CWS, EP, DP)*$$
$$P(FTH|RP, AV, EP, DP) * P(RP) * P(AV) * P(CWS) * P(EP) * P(DP) \quad (9)$$

$$P(JointProbability) = P(SRH|AV, CWS, TF) * P(SFH|AV, CWS, TF)*$$
$$P(SSH|AV, CWS, TF) * P(AV) * P(CWS) * P(TF) \quad (10)$$

The figure 7 Bayesian network depicts how the output variables International Travel Support and conferences by the department are dependent on other input and other output variables. All the funding inputs have positive impact and expenses input have negative impact on both of the output. Equation (11) is the Joint Probability of the complete network.

$$P(JointProbability) = P(CWS|RE, RF, CF, PF, NRE, VE) * P(SIT|RE, RF, CF, PF, NRE, VE)*$$
$$P(RE) * P(RF) * P(CF) * P(PF) * P(NRE) * P(VE) \quad (11)$$

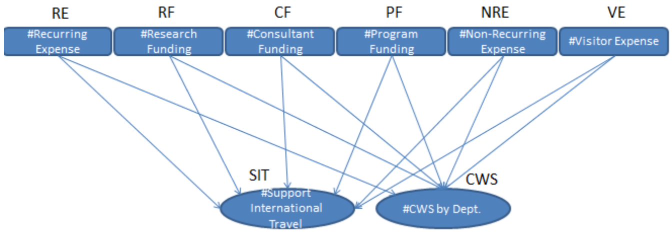

Figure 7: Bayesian Network for International Travel Support and conferences

The figure 8 Bayesian network depicts how Faculty Satisfaction is dependent on other input and other output variables. All the inputs have positive impact except too many programs as it may lead to less satisfaction due to less time on other important work. Equation (12) is the Joint Probability of the complete network.

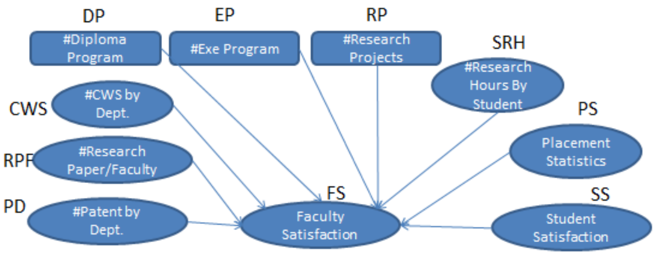

Figure 8: Bayesian Network for Faculty Satisfaction

$$P(JointProbability) = P(FS|SS, PS, SRH, RP, DP, EP, CWS, RPF, PD)* \\ P(SS) * P(PS) * P(SRH) * P(RP) * P(DP) * P(EP) * P(CWS) * P(RPF) * P(PD) \quad (12)$$

The Bayesian Networks are fed with the data tables that work as prior knowledge to the networks. For a Bayesian Network, the corresponding data table includes columns referring to each node of the network and rows have categorized values as shown in table 3. For example, for a variable number of research projects, a value of 0 signifies below an average count of projects under the department. Using learning or estimation algorithms like Maximum likelihood estimation the network learns the conditional probability of all the nodes. Using AI inferences, for example, Variable Elimination, the above conditional probability is used to infer posterior probabilities and thus do if-what/what-if analysis.

4. Simulations and Results

This section demonstrates the experimental findings of the Bayesian Network based model and how to do inferences from them. For these simulations, python language is used. Please note

Table 3
Data Table variable's value category

Category Name	Value Assigned
Below Average	0
Average	1
Above average	2

Table 4
Observation Table for Simulation Case 1

Output Variable	Below Average(0) %	Average(1) %	Above Average(2) %
Conference/Workshops	11	49	40
Support International Travel	11	49	40
Faculty Teach Hour	41	21	38
Faculty Research Hour	34	18	48
Faculty Free Hour	79	8	13
Student Free Hour	60	5	35
Student Research Hour	23	17	60
Student Study Hour	48	15	37
Research Skills	19	18	63
Research Paper per faculty	18	16	66
Placement Statistics	48	18	34
Student Satisfaction	32	31	37
Faculty Satisfaction	29	36	35

for this work, collecting data from manual records of the institute, and the department was a practical challenge. However an organisation using enterprise resource planning system can collect data and fed it to the Bayesian Network based model. Thus, below simulations have used synthetic data that are created with a logic of positive/negative dependency on each other variables.

4.1. Simulation Case 1

First Simulation is done by giving no inputs to the network that means no condition for input variables and simply learning from the data and thus giving joint probabilities of the output variables. Table 4 showing probability distribution for 3 categories.

From this simulation case 1, concerned authority can interpret that without taking any actions the institute will continue to attain below pointers for its output variables:-

- Average number of seminars, and workshops.
- With decent support for international travel, department might be more inclined towards research side with good research skills and publications.
- Though this scenario might be too busy for students and faculty.
- Placements might be below average with mixed satisfaction from the faculty and the students.

Table 5
Input Table for Simulation Case 2

Input Variable	Value	Input Variable	Value
Recurring Expenses	1	Non Recurring Expenses	2
Visitor Expenses	0	Research Funds	2
Consultant Funds	0	Program Funds	2
Research Projects	2	Research Labs	1
Executive Programs	1	Diploma Program	0
High End Equipment	1	Tech Fest	0
Patent Count	0	Faculty Count	1
Tech Staff	1	Academic Visitors	0
PhD students	2	MTech Students	1

Table 6
Observation Table for Simulation Case 2

Output Variable	Below Average(0) %	Average(1) %	Above Average(2) %
Conference/Workshops	0	0	100
Support International Travel	0	0	100
Faculty Teach Hour	28	43	29
Faculty Research Hour	0	0	100
Faculty Free Hour	100	0	0
Student Free Hour	89	4	7
Student Research Hour	0	0	100
Student Study Hour	20	20	60
Research Skills	0	0	100
Research Paper per faculty	0	0	100
Placement Statistics	31	23	46
Student Satisfaction	22	16	62
Faculty Satisfaction	1	9	90

4.2. Simulation Case 2

For the second case Table 5 is provided as the input variables to the network. Please note these values will work as condition or action taken by the authority and inference will be read as probability of a variable given these conditions.

In this simulation, input is given in a COVID-19 situation with less expenses, more research funds and projects, average staff, average new programs.

Table 6 is the observations for the output variables for the simulation case 2. Below points can be inferred by the concerned authority if actions are taken in accordance to table 5 inputs:-

- Quite good number of seminars, workshops.
- With much support for international travel, department might be totally inclined towards research side with very good research skills and publications.
- Though this scenario might be too busy for students and faculty as max time will be spent

Table 7
Input Table for Simulation Case 3

Input Variables	Value	Input Variables	Value
Recurring Expenses	2	Non Recurring Expenses	2
Visitor Expenses	1	Research Funds	1
Consultant Funds	0	Program Funds	1
Research Projects	1	Research Labs	0
Executive Programs	2	Diploma Program	2
High End Equipment	1	Tech Fest	1
Patent Count	0	Faculty Count	0
Tech Staff	0	Academic Visitors	1
PhD students	1	MTech Students	1

Table 8
Observation Table for Simulation Case 3

Output Variable	Below Average(0) %	Average(1) %	Above Average(2) %
Conference/Workshops	0	100	0
Support International Travel	0	0	100
Faculty Teach Hour	0	0	100
Faculty Research Hour	100	0	0
Faculty Free Hour	100	0	0
Student Free Hour	80	6	14
Student Research Hour	33	39	28
Student Study Hour	43	26	31
Research Skills	11	11	78
Research Paper per faculty	16	4	80
Placement Statistics	90	6	4
Student Satisfaction	45	18	37
Faculty Satisfaction	29	53	18

on research work. It might observe a balance with student time distribution between studies and research work.

- Placements might be average with quite good satisfaction from the faculty and the students.

4.3. Simulation Case 3

For the third case table 7 is provided as the input variables to the network. Please note these values will work as condition given or actions taken by the authority and inference will be read as probability of a variable given these conditions.

In this simulation, input is given as more expenses, less overall funds and projects, less staff and students, introducing new programs.

Table 8 is the observations for the output variables for the simulation case 3. Below points can be inferred by the concerned authority if actions are taken in accordance to table 7 inputs:-

- Average number of seminars, workshops.
- With complete support for international travel, department might be totally inclined towards research side with very good research skills and publications
- Though this scenario depicts less research time by the faculty and more research study by students. Faculty teaching hour are more than average in this case.
- Placements might be below average with quite good satisfaction from the faculty and the students.

4.4. How Simulations can help in decision making

Decision makers can use these simulations for various if what/what-if scenarios. A learned Bayesian Network can be subjected to various combinations of input variables and the model using AI inference methods will provide a posterior probability of the output variable of interest. If the output variables value aligns with the goals then decision makers have an evidence based action to take in order to attain the required goals. An institute with accessible data can utilize this method for evidence based decision making process.

5. Conclusion

This paper has proposed a Bayesian Network based approach to model a department, and its variables. Through simulations, we can conclude that if valid data is provided to the network based model then the network variables learn themselves and can also learn positive/negative dependency among other variables. This approach does not require prior knowledge of the complex behavior of the system thus making an academic institute's decision-making process more adaptive and data-driven. Using AI inference methods decision options can be analyzed for various what-if/if-what scenarios. For Bayesian Networks to provide valid results, correct and sufficient data is required for proper learning. This approach can further be enhanced with the inclusion of events, dynamic behavior modeling of the system, and leveling up the model for a complete institute.

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