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Ubiquitous-cloud-inspired deterministic and stochastic service provider models with mixed-integer-programming

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ABSTRACT

The ubiquitous computing system is a paradigm shift from personal computing to physical integration. This study focuses on the deterministic and stochastic service provider model to provide sub-services to computing nodes to minimize rejection values. This deterministic service provider model aims to reduce the cost of sending data from one place to another by considering the processing capacity at each node and the demand for each sub-service. At the same time, stochastic service provider aims to optimize service provision in a stochastic environment where parameters such as demand and capacity may change randomly. The novelties of this research are the deterministic and stochastic service provider models and algorithms with mixed integer programming (MIP). The test results show that the solution found meets all the constraints and the smallest objective function value. Stochastic modeling minimizes denial of service problems during wireless sensor network (WSN) distribution. The model resented is the ability of wireless sensors to establish connections between distributed computing nodes. Stochastic modeling minimizes denial of service problems during WSN distribution.

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1. INTRODUCTION

The term "ubiquitous internet of things (IoT)" describes how data is connected and exchanged anytime, anywhere [1]. The cloud is becoming a prominent research area. It is ubiquitous because it serves client needs regardless of time and place [2], such as the use of wireless sensor networks (WSN) and ubiquitous technology for intelligent agriculture with energy efficiency [3]. However, in reality, the signal from WSN is lagging, which creates uncomfortable for users. Therefore, this manuscript proposes an optimization model to overcome the problem. The model could decide the optimal base transmission station (BTS) position to minimize the disturbances.

The widespread adoption of cloud computing creates a new paradigm for work-from-home culture enterprises in the unprecedented crisis of the COVID-19 outbreak [4]. The blockchain ubiquitous manufacturing (BCUM) platform is presented to securely and reliably integrate manufacturing systems into the cloud paradigm that can provide a homogeneous and decentralized environment [5]. The deterministic model is a mathematical model that allows for reasonably accurate measurement of symptoms. Examples of deterministic model research are deterministic model studies to predict flooding [6], analysis understanding the dynamics of tuberculosis with a focus on first-line treatments such as vaccination and drug resistance [7], deterministic models for the dynamics of Q Fever transmission in dairy cattle using sensitivity analysis and optimal control Yosua [8], a deterministic model for country inventory policies for vaccine procurement [9], and a deterministic model for composable reactive systems [10].

In a stochastic model, symptoms can be identified mathematically with variable levels of accuracy. In the stochastic model, also called the probabilistic model, the probability of each event is calculated. There have been several studies on the stochastic model, including one on a plug-in hybrid electric vehicle stochastic model predictive control (MPC) technique based on reinforcement learning vehicle energy management [11] and another on a stochastic model for virtual power plants' involvement in pool markets, futures markets, and contracts with withdrawal penalties [12], a new non-geometrical stochastic model (NGSM) for non-stationary wideband vehicle communication channels is presented [13], a discrete-time stochastic epidemic model with binomial distributions to investigate the disease's transmission [14], stochastic modeling of the cutting force in turning processes [15], and a stochastic model for forecasting the novel coronavirus disease [16], and stochastic modeling reveals mechanisms of metabolic heterogeneity [17].

Mixed integer programming (MIP) is a type of mathematical optimization that involves optimizing the objective function by considering variables that can take integer (integer) values or actual (continuous) number values. In MIP, some variables may take integer values while others may take constant values [18]. There are several studies on MIP, namely Anderson *et al.* [19] proposing mixed solid integer programming formulations for modeling and analysis of trained neural networks, Schrotenboer *et al.* [20] developing MIP models for maintenance planning in wind farms offshore under conditions of uncertainty, and Belotti *et al.* [21] discussed the use of non-convex mixed integer nonlinear programming (MINLP) tightening and branching techniques. The simulation results show that the practical strategy increases the breaker's performance. The book by Wolsey and Nemhauser [22] describes combinatorial and integer optimization and the techniques used to solve these problems. This book provides a comprehensive guide on integer optimization models and methods. The book by Bertsimas and Tsitsiklis [23] describes linear optimization, which provides a complete introduction to linear optimization and optimization techniques. Tawarmalani and Sahinidis [24] discusses branch-and-cut for mixed integer linear programming (MILP) based on polyhedra and providing computational evidence of the effectiveness of this approach in global optimization problems, Marcucci and Tedrake [25] develops a warm start method in mixed-integer programs for predictive control of hybrid system models, Yu and Shen [26] develops a MIP approach distributionally robust with decision-dependent uncertainty settings, Agrawal and Bansal [27] focuses on security in the use of cloud computing in the context of education, and Krishnaraj [28] implementing a human activity monitoring system through the use of IoT sensors and the Blynk cloud platform. IoT refers to a network of physical objects connected to the internet and interacting with each other. Blynk is a cloud platform that enables developers and users to build IoT-based applications quickly.

The primary reference of this research is Tomasgard *et al.* [29] that aims to develop mathematical models and algorithms that can be used to analyze and predict the performance of distributed telecommunication networks. In a distributed telecommunications network, data and network resources are distributed across multiple geographic locations, such as distributed data centers or base stations on a cellular network. This study aims to understand the complex interactions between various elements in a distributed telecommunications network and how traffic density, network capacity, and connectivity level can affect network performance. In this study, the researchers used a mathematical modeling approach to visualize and understand the dynamics of distributed telecommunication networks. They may use techniques such as queuing theory, graph theory, or probability models to describe the behavior of networks in different situations. The results of this research can assist in planning and developing a more efficient distributed telecommunication network. For example, the developed model can be used to predict the traffic load on the web at a specific time or to identify overload points that can cause a decrease in service quality. This research can also provide insights into improving the efficient use of network resources, such as optimal network capacity or better traffic management.

The ubiquitous computing system is a paradigm shift from personal computing to physical integration. Physical integration includes material considerations in serving clients accessing cloud services. Access to cloud infrastructure at various points is branched. Network branching is caused by client access points that are close together, thus causing shared access to network hardware such as switches and routers. Access sharing can be managed using a static scheduling system that requires minimal software to apply to the limited memory of switches and routers. Static scheduling algorithms require detailed information about tasks, such as length, the quantity of jobs, and execution deadlines, as well as information about the resources to be provisioned, such as available processing power, memory capacity, and energy consumption, before (advance) execution. Due to the dynamic nature, inconsistencies in the cloud computing environment, and the volume of requests and resources, static algorithms must be revised for this type of system, as they cannot correctly adjust the workload distribution between resources.

On the other hand, dynamic scheduling, which requires more memory, is difficult to implement. To improve static scheduling performance on devices with limited memory, this research integrates deterministic and stochastic models into static scheduling so that scheduling produces better performance. The problem in creating a model is determining how to distribute subservience by counting nodes. This is done to satisfy demand using the finest resources that service providers have available. A linear MIP model of this issue is possible [30]. Sub-services are to be made available to compute nodes to decrease reject values.

2. METHOD

The research framework is a plan or structure used to organize and compile the research steps to be carried out. This framework assists researchers in designing and conducting research with clear objectives and a systematic methodology. The following research framework is shown in Figure 1.

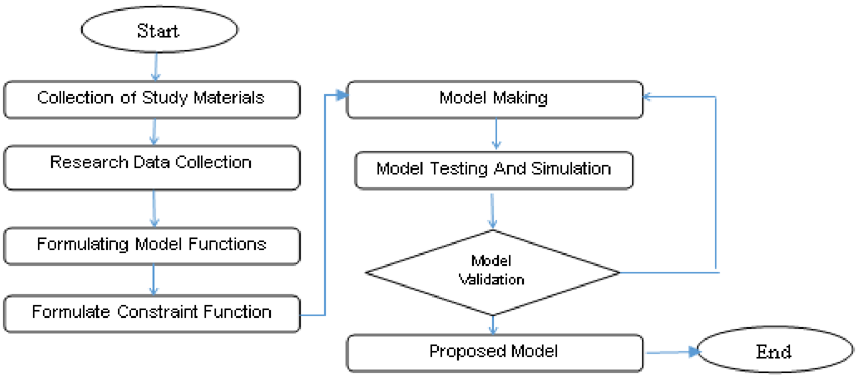


Figure 1. Research work framework

The following is an explanation of the research stages according to Figure 1:

- Collection of study materials: this stage involves gathering information, references, literature, and other resources relevant to the research topic. This study material is used to understand the issues studied and develop a theoretical framework.
- Research data collection: at this stage, the researcher collects the data needed to answer research questions or test the hypotheses that have been formulated. Data collection methods such as observation, interviews, questionnaires, or document analysis can vary.
- Formulate the model function: after the data is collected, the next step is formulating the model function. This means developing approaches or concepts that will be used to analyze or explain the data that has been collected. Model functions can be mathematical formulas, theories, or conceptual frameworks that describe the relationships between variables or constructs in research.
- Formulate constraints: this stage involves identifying and formulating obstacles that may arise in the research process. These constraints can be in the form of limited data, resources, time, or methodological problems. Defining conditions helps in devising an effective research strategy and foreseeing potential obstacles that may be encountered.
- Model building: after formulating the function of the model and identifying the constraints, the next step is building the model. This involves developing a structure or framework that systematically applies model functions to research data. Modelling also consists in selecting a technique or method of analysis appropriate to the research objective.
- Model testing and simulation: the model is tested and simulated using the relevant data at this stage. Testing and simulation aim to validate whether the model can produce accurate results by research objectives. The model can be revised or adjusted if the results do not match.
- Model validation: the model validation stage involves more comprehensive and in-depth testing to ensure that the model created can produce consistent and reliable results. Validation involves statistical analysis, comparison with previous research, and assessing the model's suitability with existing data.
- Proposed models: the final stage is to develop the proposed model based on research results and model validation. The proposed model is the final result of the research and reflects the research contribution to the field under study. This model can include policy recommendations, new frameworks, or solutions based on findings.

3. RESULTS AND DISCUSSION

The results of this study and novelties are the deterministic and stochastic service provider models for providing sub-services to computing nodes to minimize rejection values. By using this concept, the need for sub-service j in a location or another place connected to the need for the subsurface itself will be reduced. As a result, sub-service j received the bare minimum amount of requests for its processing capacity. The following is the deterministic service provider model and algorithm, as well as testing the algorithm built based on (1):

$$\min \sum_{j\in J} \pi(j)(d(j) - \sum_{i\in I} x(i,j)) \quad (1)$$

with constraints on (2)-(4):

$$\sum_{j\in J} r(i,j)z(i,j) + \sum_{j\in J} x(i,j) \leq s(i), i \in I \quad (2)$$

$$\sum_{i\in I} x(i,j) \leq d(j), j \in J \quad (3)$$

$$M(i,j)z(i,j) - x(i,j) \geq 0, (i,j) \in IxJ \quad (4)$$

where
I is computational notation set
J is subservice set
$d(j)$ is demand for service
$\pi(j)$ is get the value for sub-service j from another source
$r(i,j)$ is source for sub-service j on node I defined
$s(i)$ is total node I capacity (total capacity of node i)
(i,j) is number of requests for processing power made by assembly node I and subsurface j
$z(i,j)$ is programming connection between node I and sub-service j
$M(i,j)$ is upper limit values for variablesd (j)$-\sum_{j\in J} x(i,j)$ in the objective function is part of the subservice request j. The upper bound and lower bound for the variable $x(i,j)$ are represented by $M(i,j)$in the constraint function. $M(i,j)$ is min{ $s(i)-r(i,j), d(j)$}.

This model is a linear optimization model to minimize the cost of sending data from one place to another by considering the processing capacity at each node and the demand for each sub-service. The variables used in this model are $x(i,j)$, the Handling of capacity requests number originating from junction node I subsurface *j*, and $z(i,j)$, which in programming is the link between node I and sub-service j. Constraints in this model include: i) capacity limits on each node, ii) requests for each sub-service, and iii) upper limits for variables *x(i, j)*.

The capacity constraints at each node are defined by *s(i)* and limit the total capacity available at node *i*. The requests for each sub-service are defined by *d(j)* and *π(j)*, limiting the quantity of capacity requests received made by subsurface *j* from elsewhere. Another constraint on this model is $M(i, j)z(i, j) - x(i, j) \geq 0$, which ensures that the processing requests for capacity made by subsurface j and meeting node i do not exceed the available capacity at node *i*. The maximum for the variables *x(i, j)* the lowest bound, are defined by *M(i, j)*, which is the minimum between *s(i) - r(i, j)* and *d(j)*. This model is designed to determine the optimal allocation of processing capacity at each node to meet sub-service demands efficiently. The Algorithm can see:

1) Initialize variables and parameters
   Set *I* as a set of computational notation
   Set *J* as the subservices collection
   Set *d(j)* as a demand for assistance for j
   Set *π(j)* as the value of the subservice j request coming from another source
   Set *r(i, j)* as the specified resource for node I and subservice j
   Set *s(i)* as the power of node I overall
   Set *x(i, j)* as the quantity of handling requests for capacity produced by assembly node I and subservice j
   Set *z(i, j)* as the link programming between subservice j and node I
   Set *M(i, j)* as the maximum value for the variable
2) Calculate the lessening M (i, j) using the formula: M(i, j) = min{ s(i) - r(i, j), d(j)}
3) Define the objective function: min ∑ π(j) (d(j) − ∑ x(i, j))
4) Define the constraint function:
   $\sum r(i, j)\, z(i, j) + \sum x(i, j) \leq s(i),\ i \in I, j \in J$
   $\sum x(i, j) \leq d(j),\ i \in I, j \in J$
   $M(i, j)z(i, j) - x(i, j) \geq 0,\ (i, j) \in IxJ$

5) Use a linear programming solver to solve optimization problems with defined objective and constraint functions.
6) If the optimal solution is found, return the objective value as the solution. If not, try again with different variable values or increase the upper bound *M(i, j)* and repeat step 5.

The test results from the algorithm above are given to show that the optimal objective value is 0, and all decision variables have a value of 0. This indicates that the solution meets all the constraints and the smallest accurate function value. In general, the results of this test are good. The following is the stochastic and algorithmic service provider model as well as testing of the algorithms built on (5) and (6):

$$\min Q(Z) \sum_{j \in J} r(i,j) z(i,j) \le s(i), i \in I \tag{5}$$

$$z(i,j) \in \{0,1\}, \{i,j\} \in IxJ \tag{6}$$

The maximum number of sub-services allowed by the gusset capacity is determined by the constraint function in (7).

$$Q(Z) = E[q(z, \pi, \delta)] \tag{7}$$

The expectations for the stochastic parameters $\bar{\pi}$ and $\bar{\delta}$ on (8)-(11):

$$q(z, \pi, \delta) = \min \sum_{j \in J} \pi(j)[\delta(j) - \sum_{i \in I} x(i,j)] \tag{8}$$

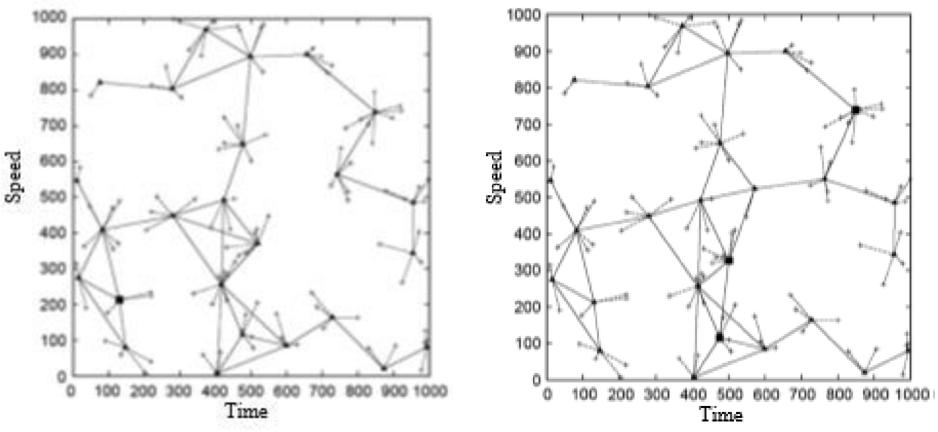
$$\sum_{j \in J} x(i,j) \le s(i) - \sum_{i \in I} r(i,j) z(i,j) = s*(i), i \in I \tag{9}$$

$$\sum_{i \in I} x(i,j) \le \delta(j), j \in J \tag{10}$$

$$x(i,j) \le M(i,j) z(i,j), (i,j) \in IJ \; x(i,j) \ge 0, (i,j) \in I \tag{11}$$

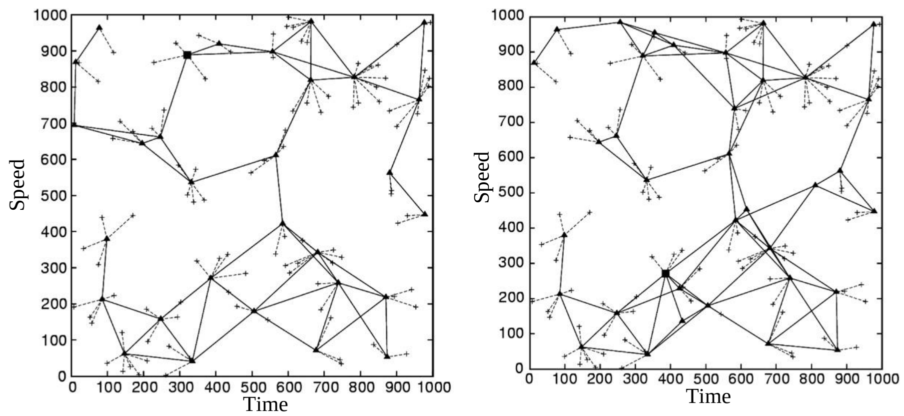
To optimize the model, the mathematical optimization algorithm is used to find the best solution for the objective function $Q(Z)$ by considering all constraint functions. The results of testing the algorithm show that this model can provide good results in optimizing service provision in a stochastic environment. The Algorithm can see:
1) Initialize variables:
   $z(i,j)$: 0 or 1, indicates whether sub-service
   j is connected to node i or not
   $x(i,j)$: integer, indicating the amount of processing capacity produced by sub-service *j* on node *i*
2) Calculate the expected value of the objective function:
   $Q(Z) = E[q(z, \pi, \delta)]$
   $q(z, \pi, \delta) = \min \sum_{j \in J} \pi(j)[\delta(j) - \sum_{i \in I} x(i,j)]$
3) Calculate the expected value for each stochastic parameterk $\overline{\pi}$ dan $\overline{\delta}$
4) Determine the the maximum amount of possible sub-services provided:
   $\sum_{i \in I} x(i,j) \le \delta(j), j \in J$
5) Determine the constraints for the variable x:
   $\sum_{j \in J} x(i,j) \le s(i) - \sum_{i \in I} r(i,j) z(i,j) = s*(i), i \in I$
   $\sum x(i, j) \le \delta(j), j \in J, i \in I$
   $x(i, j) \le M(i, j) z(i, j), (i, j) \in IxJ$
   $x(i, j) \ge 0, (i, j) \in IxJ$
6) Solve the model to find the optimal solution:
   - Minimize the $Q(Z)$ values with the constraints in steps 3 and 4.
   - Determine the values of the variables z(i, j) and x(i, j) that produce the minimum $Q(Z)$value.
7) Optimum solution output: print out the $Q(Z)$, $z(i,j)$, and $x(i,j)$values that yield the minimum $Q(Z)$ value.

The test results from the algorithm above are given to show that the optimal objective value is 0, and all decision variables have a value of 0. However, in applying the algorithm to network traffic density, it can be seen in Figure 2 which is the initial condition that has been simulated with increased traffic demand and unlimited capacity. Figure 2 is an example of a planned network obtained by fixed rate model (FRM) for the same example with two different examples of requirements on end-user traffic, d=600 Kb/s and d=3 Mb/s for all MCs, and with capacities limited from the link that connects the mesh access point (MAP) to the wired network. So that by using the optimization of the algorithm, the traffic density results are formed as shown in Figure 3. Figure 3 where the solution provided by the algorithm model is such that an increase in traffic demand implies an increase in the dimensions used to convey traffic, both in wired networks and in wireless. This indicates that the solution meets all the constraints and the smallest accurate function value. In general, the results of this test are good.



(a) (b)

Figure 2. Network traffic density level: (a) d=600 Kb/s and (b) d=3 Mb/s



(a) (b)

Figure 3. Optimal network traffic density level: (a) d=600 Kb/s and (b) d=3 Mb/s

4. CONCLUSION

Researchers have successfully built a model and algorithm for deterministic and stochastic service providers with MIP. The test results show a good value, with the optimal objective value being 0 and all decision variables having a value of 0. This indicates that the solution meets all constraints and has the smallest accurate function value. The distribution transparency model is essential for building a distributed network investment and service provider model—operational resource allocation on service provider processing nodes. The model presented is the ability of wireless sensors to establish connections between distributed computing nodes. Stochastic modeling minimizes denial of service problems during wireless sensor network distribution.

REFERENCES

[1] A. Jiang, H. Yuan, D. Li, and J. Tian, “Key technologies of ubiquitous power Internet of Things-aided smart grid,” *Journal of Renewable and Sustainable Energy*, vol. 11, no. 6, pp. 1–20, 2019, doi: 10.1063/1.5121856.
[2] D. K. A, “Review on Task Scheduling in Ubiquitous Clouds,” *Journal of ISMAC*, vol. 1, no. 1, pp. 71–79, 2019, doi: 10.36548/jismac.2019.1.006.

[3] R. Dhaya, R. Kanthavel, and A. Ahilan, “Developing an energy-efficient ubiquitous agriculture mobile sensor network-based threshold built-in MAC routing protocol (TBMP),” *Soft Computing*, vol. 25, no. 18, pp. 12333–12342, 2021, doi: 10.1007/s00500-021-05927-7.
[4] S. Mandal, D. A. Khan, and S. Jain, “Cloud-Based Zero Trust Access Control Policy: An Approach to Support Work-From-Home Driven by COVID-19 Pandemic,” *New Generation Computing*, vol. 39, no. 3–4, pp. 599–622, 2021, doi: 10.1007/s00354-021-00130-6.
[5] A. V. Barenji, Z. Li, W. M. Wang, G. Q. Huang, and D. A. Guerra-Zubiaga, “Blockchain-based ubiquitous manufacturing: a secure and reliable cyber-physical system,” *International Journal of Production Research*, vol. 58, no. 7, pp. 2200–2221, 2020, doi: 10.1080/00207543.2019.1680899.
[6] X. Jiang, H. V. Gupta, Z. Liang, and B. Li, “Toward Improved Probabilistic Predictions for Flood Forecasts Generated Using Deterministic Models,” *Water Resources Research*, vol. 55, no. 11, pp. 9519–9543, 2019, doi: 10.1029/2019WR025477.
[7] D. Otoo, S. Osman, S. A. Poku, and E. K. Donkoh, “Dynamics of Tuberculosis (TB) with Drug Resistance to First-Line Treatment and Leaky Vaccination: A Deterministic Modelling Perspective,” *Computational and Mathematical Methods in Medicine*, vol. 2021, pp. 1–14, 2021, doi: 10.1155/2021/5593864.
[8] M. Mubarak, J. Berneburg, and C. Nowzari, “Stochastic vs. Deterministic Modeling for the Spread of COVID-19 in Small Networks,” in *2021 American Control Conference (ACC)*, 2021, pp. 1346–1351, doi: 10.23919/ACC50511.2021.9482985.
[9] A. Pınarbaşı and B. Vizvári, “A deterministic model for the inventory policy of countries for procurement of vaccines,” *Central European Journal of Operations Research*, vol. 31, no. 4, pp. 1029–1041, 2023, doi: 10.1007/s10100-022-00831-3.
[10] M. Lohstroh *et al.*, “Reactors: A Deterministic Model for Composable Reactive Systems,” in *Cyber Physical Systems. Model-Based Design*, Cham: Springer, 2020, pp. 59–85, doi: 10.1007/978-3-030-41131-2_4.
[11] C. Zhang, W. Cui, Y. Du, T. Li, and N. Cui, “Energy management of hybrid electric vehicles based on model predictive control and deep reinforcement learning,” in *2022 41st Chinese Control Conference (CCC)*, 2022, pp. 5441–5446, doi: 10.23919/CCC55666.2022.9902409.
[12] A. R. Jordehi, “A stochastic model for participation of virtual power plants in futures markets, pool markets and contracts with withdrawal penalty,” *Journal of Energy Storage*, vol. 50, pp. 1–35, 2022.
[13] Z. Huang, X. Zhang, and X. Cheng, “Non-geometrical stochastic model for non-stationary wideband vehicular communication channels,” *IET Communications*, vol. 14, no. 1, pp. 54–62, 2020, doi: 10.1049/iet-com.2019.0532.
[14] S. He, S. Tang, and L. Rong, “A discrete stochastic model of the COVID-19 outbreak: Forecast and control,” *Mathematical Biosciences and Engineering*, vol. 17, no. 4, pp. 2792–2804, 2020, doi: 10.3934/MBE.2020153.
[15] G. Fodor, H. T. Sykora, and D. Bachrathy, “Stochastic modeling of the cutting force in turning processes,” *International Journal of Advanced Manufacturing Technology*, vol. 111, no. 1–2, pp. 213–226, 2020, doi: 10.1007/s00170-020-05877-8.
[16] N. Sene, “Analysis of the stochastic model for predicting the novel coronavirus disease,” *Advances in Difference Equations*, vol. 2020, no. 1, pp. 1–19, 2020, doi: 10.1186/s13662-020-03025-w.
[17] M. K. Tonn, P. Thomas, M. Barahona, and D. A. Oyarzún, “Stochastic modelling reveals mechanisms of metabolic heterogeneity,” *Communications Biology*, vol. 2, no. 1, pp. 1–9, 2019, doi: 10.1038/s42003-019-0347-0.
[18] T. Kleinert, M. Labbé, I. Ljubić, and M. Schmidt, “A Survey on Mixed-Integer Programming Techniques in Bilevel Optimization,” *EURO Journal on Computational Optimization*, vol. 9, pp. 1–21, 2021, doi: 10.1016/j.ejco.2021.100007.
[19] R. Anderson, J. Huchette, W. Ma, C. Tjandraatmadja, and J. P. Vielma, “Strong mixed-integer programming formulations for trained neural networks,” *Mathematical Programming*, vol. 183, no. 1–2, pp. 3–39, Sep. 2020, doi: 10.1007/s10107-020-01474-5.
[20] A. H. Schrotenboer, E. Ursavas, and I. F. A. Vis, “Mixed Integer Programming models for planning maintenance at offshore wind farms under uncertainty,” *Transportation Research Part C: Emerging Technologies*, vol. 112, pp. 180–202, Mar. 2020, doi: 10.1016/j.trc.2019.12.014.
[21] P. Belotti, J. Lee, L. Liberti, F. Margot, and A. Wächter, “Branching and bounds tighteningtechniques for non-convex MINLP,” *Optimization Methods and Software*, vol. 24, no. 4–5, pp. 597–634, 2009, doi: 10.1080/10556780903087124.
[22] L. A. Wolsey and G. L. Nemhauser, *Integer and combinatorial optimization*. USA: John Wiley & Sons, 1999.
[23] D. Bertsimas and J. N. Tsitsiklis, *Introduction to Linear Optimization*. Belmont, MA: Athena scientific, 1997.
[24] M. Tawarmalani and N. V. Sahinidis, “A polyhedral branch-and-cut approach to global optimization,” *Mathematical Programming*, vol. 103, no. 2, pp. 225–249, 2005, doi: 10.1007/s10107-005-0581-8.
[25] T. Marcucci and R. Tedrake, “Warm start of mixed-integer programs for model predictive control of hybrid systems,” *IEEE Transactions on Automatic Control*, vol. 66, no. 6, pp. 2433–2448, 2021, doi: 10.1109/TAC.2020.3007688.
[26] X. Yu and S. Shen, “Multistage distributionally robust mixed-integer programming with decision-dependent moment-based ambiguity sets,” *Mathematical Programming*, vol. 196, no. 1–2, pp. 1025–1064, 2022, doi: 10.1007/s10107-020-01580-4.
[27] R. Agrawal and S. Bansal, “Cloud Computing: Security with Educational Usage,” *Journal of ISMAC*, vol. 4, no. 3, pp. 165–173, 2022, doi: 10.36548/jismac.2022.3.003.
[28] N. Krishnaraj, “Implementation of a Human Activity Monitoring System through IoT Sensor and Blynk Cloud Platform,” *Journal of Information Technology and Digital World*, vol. 4, no. 2, pp. 105–113, 2022, doi: 10.36548/jitdw.2022.2.005.
[29] A. Tomasgard, S. Dye, S. W. Wallace, J. A. Audestad, L. Stougie, and M. H. van der Vlerk, “Modelling in Distributed Telecommunications Networks,” *Tinbergen Institute*, pp. 1–25, 1997.
[30] V. Nair *et al.*, “Solving Mixed Integer Programs Using Neural Networks,” *Optimization and Control*, vol. 1, pp. 1–57, 2020.

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