Artificial Intelligence-based Optimization Models for the Technical Workforce Allocation and Routing Problem Considering Productivity

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***Abstract*—Ensuring the reliability and availability of electric power networks is essential due to the increasing demands. An effective preventive maintenance strategy requires efficient resources allocation to perform the maintenance tasks, particularly the technical workforce. This paper introduces an innovative artificial intelligence-based approach to predict workforce productivity, aiming to optimize both the allocation of the technical workforce for maintenance tasks and their routing. In this study, two mathematical optimization models are introduced that utilize the output value of Artificial Neural Networks (ANN) for optimal resource allocation and routing. The first model focuses on team formation, considering the predicted productivity in order to ensure effective collaboration. While the second model focuses on the optimal assignment and routing of these teams to specific maintenance tasks. Validated with real-world data, the models show considerable promise in enhancing resource allocation, task assignment, and cost-efficiency in the electricity industry. Furthermore, sensitivity analysis has been conducted and managerial insights has been explored. The study also paves the way for future research, highlighting the potential for refining these models for more extensive applications.**

***Keywords*—Productivity; workforce; maintenance; optimization; allocation; routing**

I. Introduction

The reliability and availability of the electric power network in the electricity industry is crucial for meeting the increasing demand [1]. Many of the blackouts were confirmed to be caused by imperfect maintenance due to human factors [2]. Maintenance can be divided into two categories: corrective and preventive. Corrective maintenance is performed after a breakdown. In contrast, preventive maintenance is performed at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure [3]. Consequently, maintenance planning, and more specifically preventive maintenance is extremely important in the electricity industry and plays a major role in reducing breakdowns and avoiding expensive blackouts.

For preventive maintenance tasks to be accomplished, resources and more specifically "technical workforce" must be allocated. Resource allocation refers to the decision-making process that determines the appropriate resource to perform each task or in other words, is described as "the best person for the task" [4]. In many cases, managers manually assign workforce to tasks based on intuition and experience [5]. In addition, workforce productivity is variable and can differ based on multiple factors and more importantly based on the maintenance task to be accomplished. Therefore, predicting the workforce productivity for each task based on relevant factors and considering the workforce productivity when assigning the maintenance tasks is important for better performance.

Furthermore, the geographically dispersed nature of electricity networks necessitates the movement of technical workforce between various locations to perform maintenance tasks. While there are no published records on the time technicians spend in transition and transfer between locations within the electricity industry, it is estimated based on the authors experience to range from 15 to 40% of working time. This can significantly increase costs and reduce operational efficiency in electricity companies. Therefore, upon allocating the tasks to the technical workforce based on predicted productivity, it is important to consider the routing of the allocated teams between the task sites at the same time as the time required to accomplish the tasks.

Although many research works stated that optimal resource allocation and routing will positively affect overall productivity, however, to the best of the authors' knowledge, no previous research clearly considered the predicted labor productivity as the main criterion in the human resources assignment and routing models as it will be shown in the following section.

The aim of this study is to allocate the technical workforce into teams and then assign the formed teams to preventive maintenance tasks and to plan their routes while considering the individual technical workforce productivity predicted using ANN. Therefore, to achieve this aim, the objective of this study is to develop two mathematical optimization models that provide optimal resource allocation and routing while considering the labor productivity produced by the ANN model as an input.

Fig. 1 presents the methodological approach adopted in this study. The first optimization model focuses on forming teams by pairing employees based on their productivity metrics predicted by the ANN model. This ensures that the teams are well-balanced and can operate at their maximum potential. Indeed, in electricity maintenance, tasks are required to be performed by teams of two employees at least for company's safety requirements. In addition, in the considered case study, teams include two employees each. The second optimization model focuses on the assignment of the formed teams to specific job-locations and therefore to optimize their routing. By considering various cost components, including wages, overtime cost, and transportation cost, the model aims to find the most cost-effective strategy for the entire operation. A numerical application based on a real-world data will be conducted to validate the developed models and the integration of the ANN output as an input for the optimization models. Finally, sensitivity analysis will be conducted to examine the impact of traffic, wages, and productivity on the optimal solution.

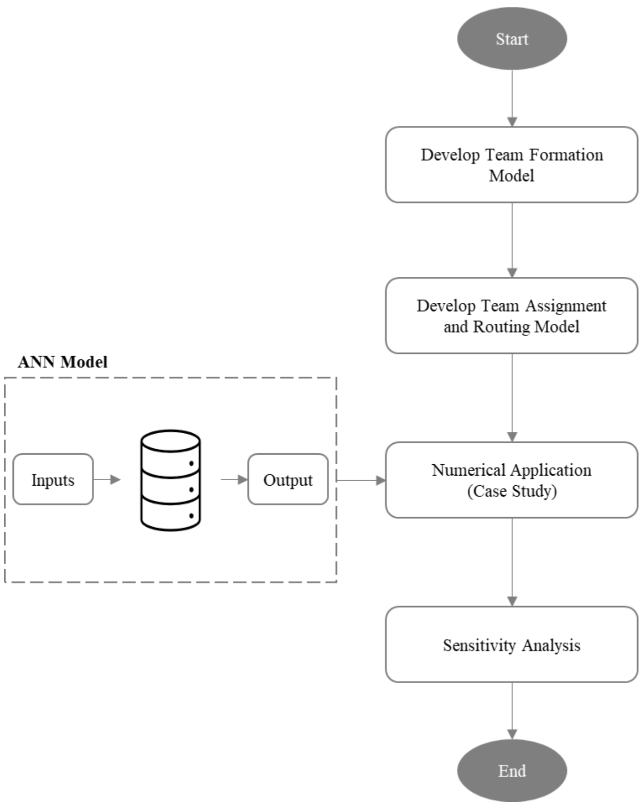

Fig. 1. The methodological approach.

The structure of this paper is organized as follows: Section II provides insight into resource assignment and routing problem related works, while Section III describes the mathematical formulation of the optimization models. Section IV focuses on the numerical application. Section V illustrates the sensitivity analysis. Finally, Section VI provides concluding remarks.

II. Literature Review

The assignment and routing of workforce is one of the important phases in the decision-making process, especially in the field of maintenance. For instance, a human resources assignment model was developed by [6] in the context of scheduling both planned and unplanned maintenance tasks. The human resources consist of three different specialties: plumber, electrician, and mechanic. The model takes into account the availability of human resources as well as support equipment, with the objective of maximizing the occupation rate of available human resources over the planning horizon. Similarly, the research work by [5] proposed a bi-objective model to assign licensed technicians to maintenance tasks across multiple work shifts. Each maintenance task must be assigned to only one technician, and only if the technician is licensed for that task. The model considers two objectives: the first is to minimize the cost for technicians to complete all the tasks, and the second is to minimize workload imbalances among technicians (ensuring workload fairness). The authors utilized a heuristic algorithm based on tabu search techniques to solve the proposed model.

In addition, a study proposed a dynamic maintenance task assignment model based on expert knowledge (experience), utilizing discrete stress–strength interference [7]. The authors employed the universal generating function method to calculate the value of experience. The objective is to determine which expert should be recommended for the corresponding maintenance task at various periods, based on the experts' values of experience, in order to maximize maintenance efficiency and reliability. A study presented the allocation and routing of technicians with different skills to perform maintenance tasks at offshore wind farms [8]. Similarly, another study proposed a manpower allocation problem in which teams of technicians with diverse skills are assigned a sequential order of tasks [9]. The model takes into account the time windows of tasks, the working hours of the staff, the skill requirements for tasks, and union regulations. A branch-and-price approach was used to solve the problem. Additionally, the same approach was employed to address the daily assignment of multi-skilled technicians into teams, tasked with maintenance along with routing and scheduling, with the objective of minimizing operational costs [10].

Another study examined the problem of maintenance planning for geographically distributed assets [11]. This research proposed a multi-objective model with the aim of minimizing total costs and maximizing the availability of the assets. The problem was addressed using a meta-heuristic solution method. The technician teaming and routing problem with service, cost, and fairness objectives was addressed in study [12]. They developed and solved mathematical optimization models for both an integrated and a sequential solution to the teaming and routing subproblems.

In the context of an electricity company, the study in [13] developed a model to assign maintenance task to a worker and to determine a schedule and route such that the downtimes of power lines and the travel effort of workers are minimized. The authors combine a Large Neighborhood Search meta-heuristic with mathematical programming techniques to solve the model. Similarly, research in [14] proposed a mixed integer programming model for multi-skilled technicians' assignment, along with the routing and scheduling problem. The aim is to form teams of technicians and assign them a sequence of planned and unplanned maintenance tasks to be performed within a given time window, depending on the type and urgency of the task. The objectives include completing higher priority tasks earlier and minimizing total operational costs.

A mixed-integer linear programming model was proposed by [15] to minimize costs associated with maintenance teams, spare parts, travel time, and noncompliance with service levels. The model was tested using various maintenance scenarios from a real maintenance provider in the UAE. The results demonstrated efficient time utilization, minimal routing schedules, and high service levels with a minimum number of teams. Recently, research in [16] explored the routing problem of preventive maintenance teams for elevator repair services, with the objective of minimizing penalties due to service earliness or lateness, assuming uniform travel times between nodes and team capability for any activity. The study developed a variable neighborhood search algorithm to solve the model.

Many of the human resource assignment problems applied in the maintenance field consider technicians' workload in the objective function. To the best of the authors knowledge, no works considered the specific problem of maintenance task assignment in the electricity industry based on labor productivity. Also, there have been no works related to this study that integrated ANN output with human resource assignment and routing problem as input.

III. Mathematical Models

A. Artificial Neural Networks Model

The ANN model has proven to be highly effective in predicting the productivity of the technical workforce, especially within the maintenance field of the electricity industry, as demonstrated in study [17]. In this study, we adopted the same configuration of the ANN model, which consisted of nine neurons in the input layer, one hidden layer with 15 neurons, and one neuron in the output layer. The activation function in the hidden layer is a sigmoid activation function (logsig), while the linear activation function (purelin) is in output layer. The model was trained using the backpropagation algorithm.

The input variables include type of equipment, employee skill level, employee health condition, level of safety measures, temperature, employee experience, level of supervisor competency, level of employee motivation or commitment, and humidity. The model aims to predict the productivity value per employee as an output parameter [17].

B. Team Formation Model

The daily planning of preventative maintenance tasks requires pairing technical workforce members into teams. Effective team formation is crucial for planning preventative maintenance to ensure tasks are executed efficiently and on schedule. This section presents the development of a team formation model, aiming to pair the members of the technical workforce into teams of two members each in a manner that minimizes disparity in productivity among them [12] [18]. The objective is not only to ensure that tasks are completed proficiently but also to prevent potential operational issues and inefficiencies that may arise from significant differences in team productivity.

The sets, parameters, decision variables, and mathematical model are described as follows:

1) Sets

$\mathcal{M}$: Set of employees indexed with $m, n = 1, \dots, M$.

$\mathcal{J}$: Set of jobs indexed with $j = 1, \dots, J$.

2) Parameters

P_{mj}: Productivity of employee m for job j; $m \in \mathcal{M}$; $j \in \mathcal{J}$.

AP_m : Average productivity of employee m; $m \in \mathcal{M}$. The average productivity is calculated using the following Equation:

$$AP_m = \frac{\sum_{j \in \mathcal{J}} P_{mj}}{J} \tag{1}$$

where:

$\sum_{j \in \mathcal{J}} P_{mj}$: is the summation of productivity values for employee m over all jobs in $\mathcal{J}$.

J: Total number of jobs.

3) Decision variables

X_{mn}: Binary variable where it is 1 if employees m and n are paired together in the same team and 0 otherwise; $m, n \in \mathcal{M}$.

dP_{mn}: A variable that represents the absolute difference in average productivity between employees m and n; $m, n \in \mathcal{M}$.

4) Mathematical model

$$\text{Minimize } \omega = \sum_{m \in \mathcal{M}} \sum_{n \in \mathcal{M}} dP_{mn} X_{mn} \tag{2}$$

Subject to:

$$\sum_{\substack{m \in \mathcal{M}, \\ m \neq n}} X_{mn} + \sum_{\substack{m \in \mathcal{M}, \\ m \neq n}} X_{nm} = 2 \qquad \forall n \in \mathcal{M} \tag{3}$$

$$X_{mn} = X_{nm} \qquad \forall m, n \in \mathcal{M} \tag{4}$$

$$dP_{mn} \geq (\ AP_m - AP_n\ )\ X_{mn} \qquad \forall m, n \in \mathcal{M} \tag{5}$$

$$dP_{mn} \geq (\ AP_n - AP_m\ )\ X_{mn} \qquad \forall m, n \in \mathcal{M} \tag{6}$$

$$X_{mn} \in \{0, 1\} \qquad \forall m, n \in \mathcal{M} \tag{7}$$

The objective function in Eq. (2) aims to minimize the sum of the absolute differences in average productivity between the members of all the formed teams. Constraint in Eq. (3) ensures that each employee is paired up with exactly one other employee. Constraint in Eq. (4) ensures the pairing is symmetrical; when an employee m is paired with an employee n, then n is paired with m. Constraint in Eq. (5) captures the non-negative difference in average productivity when employee m has a greater average productivity than employee n, and constraint in Eq. (6) captures the non-negative difference in average productivity when employee n has a greater average productivity than employee m. Together, Constraints in Eq. (5) and Eq. (6) ensure that dP_{mn} represents the absolute difference in average productivity between the two employees m and n. Constraint in Eq. (7) specifies ensures that the decision variables X_{mn} are binary.

C. Workforce Assignment and Routing Model

In the previous section, the team formation model was introduced. Now, the next stage is to assign teams to tasks and plan their routes in a way that minimizes the total cost [12]. Each team has a predicted productivity percentage per task, which affects the standard time required for the task. For example, if the team's predicted productivity is 80 percent, and the standard time for the task is 120 minutes, then the actual time will be 150 minutes, which is obtained by dividing the standard time by the productivity. Not all teams need to be assigned, but if a team is assigned, they are required to start their work from a designated depot and must return to it before the end of the regular working time. If a team returns after this designated time, overtime costs will be incurred.

The sets, parameters, decision variables, and mathematical model are detailed as follows:

1) Sets

$\mathcal{T}$: Set of teams indexed with $t = 1, \dots, T$.

$\mathcal{J}$: Set of job-locations indexed with $i, j = 1, \dots, J$.

$\mathcal{J}_0$: Set of job-locations to which the depot (where all teams start and end their routes) is added indexed with $i, j = 0, \dots, J$.

It is worth noting each job-location is a location (i.e. a node) in the network at which only one job is to be performed. This is usual in electricity preventive maintenance where each location has a job performed by one team. Moreover, two different job-locations may correspond to the same type of maintenance tasks located in two different locations.

2) Parameters

dH_j : Standard time (minutes) required to complete the maintenance work of job-location j regardless of productivity of the team that will be assigned; $j \in \mathcal{J}$. It corresponds to the earned hours.

P_{tj} : Productivity of team t in performing job j; $t \in \mathcal{T}$; $j \in \mathcal{J}$. This value is derived from the ANN model mentioned in Section III.A [17]. It corresponds to the minimum productivity value of all the team members for job j.

F_t^v : Variable cost per hour of team t; $t \in \mathcal{T}$

F_{ij}^r : Transportation cost per team from job-location i to job-location j; $i, j \in \mathcal{J}_0$.

F_t^o : Overtime cost per hour for team t; $t \in \mathcal{T}$

T_{ij}^r : Time (Minutes) required to move from job-location i to job-location j; $i, j \in \mathcal{J}_0$.

$\mathcal{H}$: Number of regular working hours per day.

α : Maximum number of overtime hours per day for each team.

$\mathcal{S}$: Very large positive number.

3) Decision variables

Z_{tij}: Binary variable that is equal to 1 if team t performs the work in job-location (i.e., job) i directly before job j and 0 otherwise; $t \in \mathcal{T}$; $i, j \in \mathcal{J}$.

WT_t: Total number of regular working hours spent by team t per day; $t \in \mathcal{T}$.

O_t: Total number of overtime hours spent by team t per day; $t \in \mathcal{T}$.

f_j: Completion time of job-location j; $j \in \mathcal{J}$.

4) Mathematical model

Minimize $\mathcal{X}$

$$= \sum_{t \in \mathcal{T}} F_t^v \, WT_t + \sum_{t \in \mathcal{T}} F_t^o \, O_t + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{J}_0} \sum_{j \in \mathcal{J}_0} F_{ij}^r \, Z_{tij} \quad (8)$$

Subject to:

$$\sum_{j \in \mathcal{J}} Z_{t0j} \le 1 \qquad \forall t \in \mathcal{T} \quad (9)$$

$$\sum_{i \in \mathcal{J}} Z_{ti0} \le 1 \qquad \forall t \in T \quad (10)$$

$$\sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{J}_0} Z_{tij} = 1 \qquad \forall j \in \mathcal{J} \quad (11)$$

$$\sum_{i \in \mathcal{J}_0} Z_{tij} = \sum_{i \in \mathcal{J}_0} Z_{tji} \qquad \forall t \in \mathcal{T}, j \in \mathcal{J}_0 \quad (12)$$

$$\sum_{i \in \mathcal{J}_0} \sum_{j \in \mathcal{J}_0} \left(T_{ij}^r + \frac{dH_j}{P_{tj}}\right) \times Z_{tij} = WT_t + O_t \qquad \forall t \in \mathcal{T} \quad (13)$$

$$f_i + T_{ij}^r + \frac{dH_j}{P_{tj}} \le f_j + \mathcal{S} \times \left(1 - Z_{tij}\right) \qquad \forall t \in \mathcal{T}, \; i \in \mathcal{J}_0, j \in \mathcal{J} \quad (14)$$

$$f_j \ge 0 \qquad \forall j \in \mathcal{J}_0 \quad (15)$$

$$WT_t \le \mathcal{H} \qquad \forall t \in \mathcal{T} \quad (16)$$

$$O_t \le \alpha \qquad \forall t \in \mathcal{T} \quad (17)$$

$$Z_{tij} \in \{0, 1\} \qquad \forall t \in \mathcal{T} \quad (18)$$

The objective function in Eq. (8) minimizes the total cost in order to find the most cost-effective strategy for teams' assignment and routing, taking into consideration three pivotal cost components. The first component is associated with the cost of regular working hours of each team, capturing the standard wage or payment the team t would receive during regular working hours. The second component is associated with the cost of overtime hours of each team t. This factor represents the additional expense that might be incurred when teams work beyond standard working hours. The last component is the transportation cost for every move from location i to location j. In other words, the objective function ensures that tasks are allocated to teams and routed in the most economically efficient manner, balancing work hours, overtime, and travel expenses.

Constraints in Eq. (9) and Eq. (10) ensure that each team should start and end their route at the depot at most once. Constraint in Eq. (11) states that each job-location is visited once by one of the teams. Constraint in Eq. (12) guarantees that each team visiting a node j also leaves this node. Constraint in Eq. (13) specifies the value of the working hours and overtime hours of each team, which is composed of the traveled times and job time considering team productivity. Constraint in Eq. (14) defines the time at which job j is completed by team t. It requires that the completion time of the proceeding job i plus the travel time from i to j and the processing time of job j is a lower bound for the completion time of job j. In this constraint $\mathcal{S}$ denotes a sufficiently large positive value. Constraint in Eq. (15) ensures non-negative completion time. Constraint in Eq. (16) ensures that a team's regular working hours in a day do not exceed the maximum limit, while Constraint in Eq. (17) ensures that the overtime hours a team can work in a day should not exceed the maximum limit set by the organization's policy. Constraint in Eq. (18) specifies the domain of the decision variable.

IV. NUMERICAL STUDY

In this section, the team formation and team assignment and routing models will be applied to the specific real-world context of preventive maintenance planning within a large electricity company that is responsible for generating, transmitting, and distributing power. Subsequent subsections will illustrate the details of the data collected. The numerical application serves as a demonstration of how these models can be effectively utilized to optimize preventive maintenance planning in the electricity industry and what kind of results can be expected.

A. Team Formation

1) Inputs data: In this stage, the focus is on forming teams based on the predicted productivity of each employee for each job. Initially, details about the maintenance jobs required to be performed are obtained. These details represent the maintenance jobs for a day within one zone. To ensure a robust validation of the model, the selected day had the highest number of jobs in that zone during a year. Subsequently, the ANN model developed in [17] and discussed above is employed to predict productivity of each employee for each maintenance job. The ANN model was executed after gathering and normalizing the necessary inputs data. Table I presents the predicted productivity values (P_{mj}).

2) Results: The developed mathematical model for team formation has been solved using IBM ILOG CPLEX optimization software, with a computation time of 1.05 seconds, using Intel Core i7 at 3.70 GHz computer with 16 GB RAM. the optimal team formation has been determined with an optimal objective value of $\omega^* = 0.277$. Table II displays the team formation results (X_{mn}).

TABLE I. PREDICTED PRODUCTIVITY VALUE PER EMPLOYEE PER JOB

m \ j	1	2	3	4	5	6	7	8	9	10	11
1	1.361	1.057	1.057	1.057	1.361	1.361	1.262	1.361	1.361	1.226	1.361
2	1.236	1.071	1.071	1.071	1.236	1.236	1.114	1.236	1.236	1.161	1.236
3	1.019	0.794	0.794	0.794	1.019	1.019	0.960	1.019	1.019	1.033	1.019
4	1.056	1.128	1.128	1.128	1.056	1.056	1.018	1.056	1.056	0.998	1.056
5	1.085	1.207	1.207	1.207	1.085	1.085	1.032	1.085	1.085	1.065	1.085
6	1.080	0.808	0.808	0.808	1.080	1.080	1.009	1.080	1.080	1.058	1.080
7	0.875	0.605	0.605	0.605	0.875	0.875	0.969	0.875	0.875	0.803	0.875
8	1.120	0.833	0.833	0.833	1.120	1.120	1.042	1.120	1.120	1.078	1.120
9	1.056	1.018	1.018	1.018	1.056	1.056	1.005	1.056	1.056	0.915	1.056
10	1.190	1.106	1.106	1.106	1.190	1.190	1.147	1.190	1.190	1.128	1.190
11	1.177	1.082	1.082	1.082	1.177	1.177	1.191	1.177	1.177	1.080	1.177
12	1.162	1.502	1.502	1.502	1.162	1.162	1.077	1.162	1.162	1.293	1.162
13	1.120	0.833	0.833	0.833	1.120	1.120	1.042	1.120	1.120	1.078	1.120
14	1.063	1.152	1.152	1.152	1.063	1.063	1.016	1.063	1.063	1.026	1.063
15	1.008	0.797	0.797	0.797	1.008	1.008	0.951	1.008	1.008	1.030	1.008
16	1.041	0.915	0.915	0.915	1.041	1.041	1.057	1.041	1.041	0.966	1.041

TABLE II. TEAM FORMATION RESULTS

No.	Employee (m)	Employee (n)	Absolute difference in average productivity between employees (dP_{mn})
1	1	12	0.002090909090908
2	2	10	0.015545454545455
3	3	6	0.043818181818182
4	4	14	0.012727272727273
5	5	11	0.031909090909091
6	7	15	0.143909090909091
7	8	13	0.000000000000000
8	9	16	0.026909090909091

B. Workforce Assignment and Routing

1) Inputs data: The data acquired regarding the maintenance jobs to be performed are utilized, along with additional information and details. Using the team formation results, team productivity values have been determined based on the lowest predicted productivity among its members. Table III displays the predicted productivity values of each team for each job (P_{tj}). The daily duration of regular working time for each team is set at eight hours per day ($\mathcal{H}$), while the maximum allowable overtime per team is limited to two hours per day (α). Team regular cost (F_t^v) and team overtime cost (F_t^o) in AED per hour are illustrated in Table IV. Moreover, Table V presents the standard time required to complete the maintenance jobs in minutes (dH_j). This standard time was established by the maintenance department of the selected company, assuming that all teams will perform at the same productivity level. Another critical dataset required for team routing is the transportation time matrix and transportation cost matrix. These matrices provide a systematic representation of time and cost associated with moving between different job-locations. Table VI displays (T_{ij}^r) the transportation times between job-locations that teams must traverse to perform maintenance tasks, while Table VII presents (F_{ij}^r) the transportation costs between these locations. The transportation cost is derived from the actual distances between job-locations obtained from [19]. For each kilometer of distance, the cost is calculated by considering both the average fuel expense and other vehicle-related expenses. It is worth noting that transportation time and cost between locations are not symmetric. For example, moving from job-location (2) to job-location (3) takes 19 minutes, but moving from job-location (3) to job-location (2) takes 29 minutes. Finally, the very large positive number ($\mathcal{S}$) has been set to 10,000.

TABLE III. PREDICTED PRODUCTIVITY VALUE PER TEAM PER JOB (P_{tj})

t \ j	1	2	3	4	5	6	7	8	9	10	11
1	1.162	1.057	1.057	1.057	1.162	1.162	1.077	1.162	1.162	1.226	1.162
2	1.190	1.071	1.071	1.071	1.190	1.190	1.114	1.190	1.190	1.128	1.190
3	1.019	0.794	0.794	0.794	1.019	1.019	0.960	1.019	1.019	1.033	1.019
4	1.056	1.128	1.128	1.128	1.056	1.056	1.016	1.056	1.056	0.998	1.056
5	1.085	1.082	1.082	1.082	1.085	1.085	1.032	1.085	1.085	1.065	1.085
6	0.875	0.605	0.605	0.605	0.875	0.875	0.951	0.875	0.875	0.803	0.875
7	1.120	0.833	0.833	0.833	1.120	1.120	1.042	1.120	1.120	1.078	1.120
8	1.041	0.915	0.915	0.915	1.041	1.041	1.005	1.041	1.041	0.915	1.041

TABLE IV. REGULAR COST (F_t^v) AND OVERTIME COST (F_t^o) PER TEAM

Team Number	Regular Cost [AED/Hour]	Overtime Cost [AED/Hour]
1	425.00	531.25
2	350.00	437.50
3	460.00	575.00
4	310.00	387.50
5	350.00	437.50
6	425.00	531.25
7	425.00	531.25
8	385.00	481.25

TABLE V. THE STANDARD TIME FOR EACH JOB-LOCATION (dH_j)

Job-Location	Standard Time [Minutes]
1	160
2	90
3	90
4	90
5	130
6	160
7	190
8	130
9	150
10	120
11	120

TABLE VI. TRANSPORTATION TIME MATRIX [MINUTES]

i \ *j*	Depot	1	2	3	4	5	6	7	8	9	10	11
Depot	0.0	33.0	20.0	34.0	35.0	38.0	37.0	39.0	39.0	40.0	33.0	34.0
1	35.0	0.0	28.0	20.0	12.0	22.0	17.0	17.0	22.0	21.0	17.0	25.0
2	17.0	25.0	0.0	19.0	23.0	23.0	25.0	25.0	27.0	26.0	23.0	20.0
3	37.00	19.00	29.0	0.0	12.0	11.0	12.0	16.0	11.0	13.0	21.0	13.0
4	35.00	15.00	28.0	12.0	0.0	15.0	10.0	10.0	16.0	14.0	14.0	20.0
5	36.0	26.0	31.0	12.0	17.0	0.0	13.0	16.0	6.0	14.0	20.0	17.0
6	38.0	17.0	25.0	12.0	11.0	13.0	0.0	7.0	14.0	10.0	15.0	23.0
7	36.0	19.0	28.0	14.0	12.0	15.0	6.0	0.0	15.0	13.0	17.0	23.0
8	41.0	25.0	31.0	12.0	18.0	3.0	15.0	17.0	0.0	12.0	22.0	20.0
9	39.0	23.0	33.0	12.0	13.0	15.0	9.0	13.0	16.0	0.0	17.0	22.0
10	36.0	11.0	25.0	19.0	14.0	21.0	15.0	18.0	21.0	20.0	0.0	25.0
11	26.0	19.0	18.0	13.0	16.0	18.0	16.0	18.0	18.0	18.0	17.0	0.0

TABLE VII. TRANSPORTATION COST MATRIX [AED]

i \ *j*	Depot	1	2	3	4	5	6	7	8	9	10	11
Depot	0.0	22.5	10.0	20.0	20.0	21.0	22.5	22.0	21.5	22.5	21.0	19.0
1	29.5	0.0	14.5	6.0	3.3	10.0	5.5	5.0	10.5	7.5	5.5	10.0
2	8.5	13.0	0.0	11.5	12.0	12.5	14.0	13.5	13.0	14.0	15.0	10.5
3	19.5	10.0	12.5	0.0	2.6	3.7	4.6	4.6	4.0	4.2	8.0	3.2
4	25.5	3.1	12.5	2.8	0.0	8.0	3.4	3.0	8.5	5.0	6.0	4.6
5	20.0	14.0	13.0	4.1	5.5	0.0	5.0	5.5	0.6	5.5	11.5	5.5
6	21.5	5.0	14.5	4.1	3.2	5.0	0.0	1.5	5.5	2.3	8.5	7.0
7	21.0	5.0	14.0	4.7	3.0	5.5	1.3	0.0	6.0	2.9	8.5	6.0
8	21.0	8.0	14.0	3.3	4.9	1.2	4.3	5.0	0.0	2.4	11.0	6.0
9	25.0	12.0	18.5	3.7	3.7	5.5	3.4	4.1	5.5	0.0	10.0	8.0
10	22.5	4.3	17.0	10.5	6.0	11.5	8.0	8.0	12.0	9.0	0.0	10.5
11	16.5	6.5	9.5	3.3	5.0	8.0	7.5	7.0	8.0	7.5	8.5	0.0

TABLE VIII. TEAM ASSIGNMENT AND ROUTING RESULTS

Team Number	The Sequence of Performing Job-Location	Working Time [Minutes]	Overtime [Minutes]
Team 2	Depot – 6 – 9 – 8 – 5 – Depot	480	100.99
Team 4	Depot – 2 – 3 – 4 – 7 – Depot	480	43.37
Team 5	Depot – 10 – 1 – 11 – Depot	465.74	0

2) Results: Using the developed mathematical model, the optimal assignment and routing have been obtained with a total optimal cost of 9,164.56 AED. Table VIII shows the sequence of job-locations to be visited and performed, total working time, and total overtime by each of the assigned teams. Note that five teams, specifically, teams number 1, 3, 6, 7, and 8 will not be assigned to any preventive maintenance task and will be supporting the emergency function. The model has been solved using IBM ILOG CPLEX optimization software, with a computation time of 14608.77 seconds, using Intel Core i7 at 3.70 GHz computer with 16 GB RAM.

V. Sensitivity Analysis

A. Impact of the Trasportation Time (Traffic) on the Optimal Solution

To study the impact of the transportation time (traffic) on the optimal solution, we increased the transportation time to consider different traffic scenarios, while maintaining the other parameters equal to their values considered in the original data set. The value of T_{ij}^{r} has been changed in each trial for selected routes based on the actual traffic condition corresponding to the expected time at which the team will travel from job-location i to j. The model has been solved for every change in the travelling time and the optimal solution has been obtained and noted. Fig. 2 identifies the effect of changing the transportation time (traffic) on the objective value (total cost). The results of each trial are detailed in Table IX. The sensitivity analysis reveals that the model is notably influenced by variations in transportation time, impacting not only the cost but also the optimal routing sequences. The working and overtime hours also showcased sensitivity to changes in transportation time, albeit with varied impact across different teams and trials.

TABLE IX. Detailed Results of the Effect of Traffic Time on Optimal Solution

Trial	Traffic Time [Minutes]	Total Cost [AED]	CPU Time [Seconds]	Team Number	Optimal Sequence of Job-Locations	Working Time [Minutes]	Overtime [Minutes]
1	18	9195.14	18360.31	Team 2	Depot – 5 – 8 – 9 – 6 – Depot	480	101.99
				Team 4	Depot – 3 – 4 – 7 – 2 – Depot	480	47.37
				Team 5	Depot – 10 – 1 – 11 – Depot	465.74	0
2	38	9216.30	26215.47	Team 2	Depot – 5 – 8 – 9 – 6 – Depot	480	101.99
				Team 4	Depot – 3 – 4 – 7 – 2 – Depot	480	47.37
				Team 5	Depot – 11 – 10 – 1 – Depot	467.74	0
3	90	9222.17	15859.78	Team 2	Depot – 8 – 5 – 9 – 6 – Depot	480	101.99
				Team 4	Depot – 4 – 7 – 3 – 11 – Depot	480	78.22
				Team 5	Depot – 1 – 10 – 2 – Depot	435.32	0
4	124	9320.80	24970.38	Team 2	Depot – 9 – 6 – 5 – 8 – Depot	480	107.99
				Team 4	Depot – 7 – 3 – 11 – 2 – Depot	480	81.22
				Team 5	Depot – 10 – 1 – 4 – Depot	441.32	0
5	202	9453.31	31804.34	Team 2	Depot – 1 – 8 – 5 – 11 – Depot	480	95.78
				Team 4	Depot – 2 – 3 – 4 – 7 – Depot	480	54.37
				Team 5	Depot – 10 – 6 – 9 – Depot	480	22.39

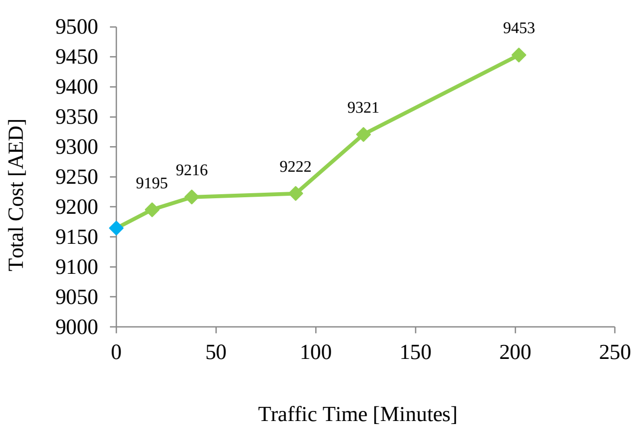

Fig. 2. The effect of traffic time on total cost.

B. Managerial Insights

The sensitivity analysis conducted underscores the substantial impact that transportation time can have on total costs. Notably, the correlation between increased transportation time and higher costs necessitates a proactive approach to traffic management by decision-makers. Managers should not only be vigilant about traffic conditions but also develop comprehensive strategies to mitigate their impact, as follows:

1) Avoiding peak traffic hours in the morning and afternoon. For example, teams could start at 6:00 AM instead of 7:30 AM.

2) Utilizing real-time traffic applications such as Google Maps can assist in identifying the most efficient paths and anticipating traffic bottlenecks, allowing for preemptive route adjustments.

3) Implementing flexible scheduling systems that adapt in real-time to traffic conditions can minimize unproductive hours spent in transit.

4) Considering the introduction of a second depot; the location of this depot should be informed by a thorough analysis of historical data on traffic patterns, job locations, and team movements to determine the most effective placement.

VI. Conclusion

In this study, team formation and team assignment and routing models that consider teams productivity based on ANN have been presented. The team formation model aimed to minimize the disparity in productivity among the members of each team. This is crucial in the context of maintenance as disparity can lead to inefficiencies, missed schedules, and potential operational disruptions. The objective of the team assignment and routing model was to minimize costs associated with regular working time, overtime, and transportation. Ensuring an economical approach to task assignment and routing is fundamental to operational efficiency, cost savings, and meeting maintenance schedules.

The real-world numerical application fortifies the practical applicability of the proposed models. In the context of an electricity company, the models showcased how one can optimize preventive maintenance planning, leading to improved resource utilization and cost-effectiveness. The rapid computation time, even for real-life sized scenarios, also underscores the feasibility of incorporating such models in everyday operational decisions. Furthermore, sensitivity analysis has been conducted to examine the effects of transportation time (traffic) on the optimal solution. It was noticed that increases in transportation time significantly raised total costs. The analysis revealed that longer travel times, often due to traffic congestion, directly correlate with increased expenses, highlighting the need for efficient route planning and traffic management strategies.

Future research may consider implementing many possible changes to the developed model. For Instance, includes outages time window. Additionally, future research should also aim to address the limitations of this study, such as the potential to use heuristics approaches in order to find the optimal solution for all the zones instead of only one zone at the same time.

Acknowledgment

The authors express their sincere gratitude to the experts who provided invaluable opinions and contributions to this study.

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