Digitalization Challenges: A Decision-Making Model for SCADA Systems Staff Selection

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Abstract: - The article examines the issues related to industrialization and more precisely the main driver of digital transformation namely people. Industry 5.0 through digitization focuses on promoting sustainability and the need for social and individual well-being. The most important factor in digital transformation is people, not technology. And here is the main problem – there are not enough people with skills to support high-tech systems such as SCADA. For this goal, a decision-making model in the selection of staff for SCADA systems support is proposed. The applicability of the model is used in the selection of staff to support a SCADA system of a small airport with the primary goal of detection and recognition of moving objects. The obtained results are encouraging and give confidence about the applicability of the proposed model.

Key-Words: digitalization challenges; decision making; mathematical model; SCADA; staff selection; evaluation criteria.

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1 Introduction

With the emergence of Industry 4 and Industry 5 in recent years, ongoing digital industrial transformation can be identified in various applications in industrial areas, [1], [2]. Industry 5.0 through digitization and technology emphasizes the promotion of sustainability and foregrounds the need for both social and individual well-being. Therefore, digital transformation is directly related to the adoption of disruptive technologies that increase not only productivity but also lead to improved social welfare, [3]. The most important factor in digital transformation is not technology, but people. And here is the main problem: there are not enough people with the skills to engage with the challenges that new digital technologies pose.

Ones of the most important systems contributing to industrial digitalization are the SCADA (Supervisory, Control and Data Acquisition) systems, designed for remote supervision, control and optimization of industrial processes, with the ability to integrate data collected from various industrial processes and automata. Control and data collection systems aim to improve the efficiency of industrial control systems while also providing better protection of the equipment used, [4], [5]. SCADA and industrial control systems play an essential role in managing and controlling critical infrastructures. The list of critical infrastructures varies in different countries and could include nuclear reactors, transportation including airports, chemical/civil engineering, water plants, wind and photovoltaic farms, agriculture, healthcare, research, etc. SCADA contributes to facilitating the seamless flow of data essential for monitoring, control, decision-making, and more.

Along with Industries 4.0 and the Industrial Internet of Things (IIoT) evolution, contemporary SCADA systems rely on different technologies including cloud technology [6], big data analytics [7], [8], artificial intelligence [9], [10], and machine learning, [11], [12], [13].

Some of the opportunities, challenges, and potential solutions to the challenges of integrating

IIoT into existing SCADA systems are discussed in [14]. The use of these technologies contributes to improving interoperability, easing maintenance, and thus decreasing the infrastructure cost, [15]. In a review paper, the authors analyze SCADA system architectures and implemented communication protocols to understand and highlight the need for the security of SCADA systems, [16].

In addition, the need for technological resilience of cyber assets should be mentioned, which can only be achieved in the presence of well-trained and motivated specialists, [17]. It should also be noted that the weakest link in the security chain is the human being, which can be either a user, a customer, an administrator, or even a manager, [18]. Therefore, technological progress needs competent users/operators with the necessary skills to perform not only routine procedures but also decision-making in critical situations, [19].

Personnel recruitment refers to a systematic process of evaluating and selecting the most qualified candidates from a given number for a particular position, [20], [21]. In this regard, the current article proposed a model to support decision-making in selecting of staff to support SCADA systems. The recent investigation describes the most common uses of machine learning in personnel selection, along with some challenges to adopting machine learning in personnel selection, [22]. In contrast to the variety of approaches for the selection of personnel, [23], [24], [25], the proposed model is formulated to be easy and flexible to cope with the problem of selection of staff to support SCADA systems.

The rest of the paper follows the following structure: Section 2 provides basic information about key indicators important in the staff selection considering SCADA systems, Section 3 describes the proposed model for evaluation and selection of the most reliable candidates to support SCADA systems; Section 4 contain the data for numerical testing; Section 5 describes the obtained results and discussion and the conclusion is drawn in Section 6.

2 Groups of Criteria to Evaluate Candidates to Support SCADA Systems

SCADA systems differ for different specific industries and applications but it is easy to identify some commonly supported functionalities such as:

- Data collection is a basic functionality of SCADA systems because thanks to the sensors it becomes possible to collect the data transmitted to the field controllers, which in turn transmit them to the SCADA computers.
- Another basic functionality is remote control, which is achieved by controlling field actuators and the data received from field sensors via sensor networks. The sensors and actuators have to work in sync in collecting and sending data and this should be properly reflected in all sensed data.
- Through network communication, it is possible to implement all SCADA functionalities. The data collected from the sensors through the SCADA field controllers is transmitted to the SCADA monitoring computers. In the opposite direction – remote control instructions are transmitted from the SCADA monitoring computers to the actuators.
- Data presentation, which is the process of visualizing both current and historical data to the operators controlling the SCADA system, is implemented through appropriately designed human-machine interfaces.
- Real-time processing and visualization combined with historical data are important for SCADA systems. This is because based on this data, operators can track and make decisions based on current state trends versus historical ones.
- Alert alarms in SCADA systems are designed to promptly inform operators of potential anomalies in the system. These alarms are configured to notify operators of stalled processes, malfunctions, or situations where SCADA processes need to be stopped, started, or corrected.
- Reporting in SCADA systems. This functionality refers to the generation and distribution of reports based on collected data. These reports can be customized for various specific uses and could include various information, such as operational status, alarms, performance metrics, and trends.

SCADA systems work with a real-time operational database that presents both current and past values used to monitor and control the operation. Databases play a crucial role in the storage and management of historical data, as they enable the retrieval of historical data used to analyze trends, optimize processes, and make strategic decisions. Therefore, security is vital for SCADA systems, as in most cases access to databases is remote. The use of firewalls, encryption, authentication, and appropriate access controls is mandatory to protect data and infrastructure. This means that operational staff must be aware of security measures against data breaches and cyber-attacks.

To be efficient and effective, the most reliable candidate has to be able to handle various technologies related to sensors and signal processing, communication protocols, data mining, and decision-making and specifics of the application area as shown in Figure 1.

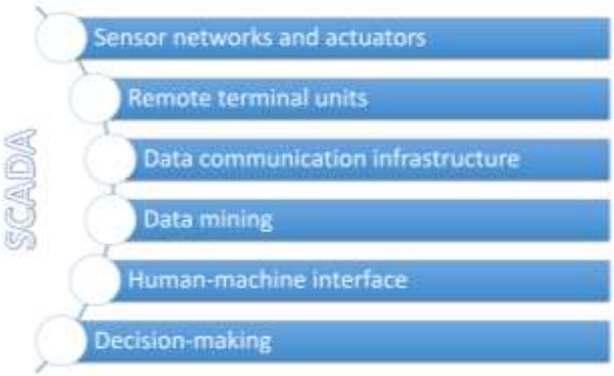

Fig. 1: Knowledge of various technologies for SCADA

Knowledge related to the sensors networks and actuators is required as the SCADA systems collect data from multiple units to measure temperature, pressure, flow rate, voltage, and other characteristics and then send it to a central computer system. The collected data is transmitted securely via a remote terminal unit to a dedicated server or cloud. Next, the data needs to be properly processed and interpreted to retrieve the trends by a suitable method such as statistics, machine learning, big data analytics, etc. to get the information. This information needs to be analyzed additionally with the help of suitable decision-making models that decisions will contribute to determining the final decision. The connection between field instruments that collect sensor data, controllers, and central SCADA computers is made through the communication infrastructure, allowing operators to visualize current and historical data in the human-machine interface. This process must necessarily be in accordance with the subject area in which SCADA is implemented. This theoretical knowledge would not be useful if the candidate failed to demonstrate its application in practice.

Along with the required knowledge, the preferred candidate should also possess additional skills such as good verbal and written communication, active listening; teamwork which is a critical factor for the success of any business; awareness; ability, and readiness to develop, organize, and run a business processes/project; ability to conflict and stress management; motivation; time management; confidence building; decision making, etc.

All this means that the indicators for evaluation and selection of the most preferred candidate for managing the SCADA system can be grouped into the following three groups of criteria:

- Theoretical knowledge: sensor networks, controllers, signal processing techniques, database, data analysis, big data mining algorithms, machine learning techniques and algorithms, programming language/s, human-machine interface, models for decision-making, etc.
- Soft skills: verbal and written communication, active listening, working in a team, conflict management, strategic thinking, creativity, ability to manage stress, initiative, curiosity planning, flexibility discipline, deductive reasoning and synthesis, confidence building, problem-solving, empathy, social skills, etc.
- Problem-solving – solving specific practical cases.

It should be noted, that hard skills and practical problem-solving can be much easier to identify because they could be assessed using appropriate tests, [26]. Soft skills are highly subjective and require interviews through which it is possible to ascertain some of these skills.

These three types of criteria sets appear to be useful as evaluation criteria in the selection of personnel to maintain SCADA systems.

3 Mathematical Model for Assessment and Selection of the Most Reliable Candidate for Support SCADA Systems

To assess candidates for supporting the SCADA systems it is necessary to consider three separate groups of criteria concerning theoretical knowledge, soft skills, and practical problem-solving. This is realized through the proposed mathematical model for the assessment of the performance of candidates (C^i), formulated as follows:

$$C^i = \max\left\{\alpha \sum_{t=1}^{T} w_t e_{it} + \beta \sum_{s=1}^{S} w_s e_{is} + \right. \\ \left. + \gamma \sum_{p=1}^{P} w_p e_{ip}\right\} \quad (1)$$

$$\alpha + \beta + \gamma = 1 \quad (2)$$

$$\sum_{t=1}^{T} w_t = 1 \quad (3)$$

$$\sum_{s=1}^{S} w_s = 1 \quad (4)$$

$$\sum_{p=1}^{P} w_p = 1 \quad (5)$$

where $i = \{1,2, \ldots, N\}$ is used to denote the set of candidates, coefficient α is used to denote the importance of theoretical knowledge, coefficient β is used to denote the soft skills, while the coefficient γ expresses the practical problem-solving.

The coefficients w_t, w_s, and w_p are used to denote the importance of criteria related to theoretical knowledge, soft skills, and practical problem-solving. The evaluation score of i-th candidate about the t-th criterion is denoted by e_{it}, e_{is} expresses scores of i-th candidate about the s-th criterion regarding soft skills, while e_{ip} expresses scores of i-th candidate about the p-th criterion regarding practical problem-solving.

The allowable interval of the evaluation scores e_{it} a e_{is}, and e_{ip} should be identical to the variation interval of the other variables in the proposed model (1) – (5). Therefore, the interval between 0 and 1 can ensure that comparable values are obtained, and is therefore considered an acceptable variation interval. Using the relation (2) it is possible to aggregate the separated three parts of evaluation regarding theoretical knowledge, soft skills, and practical problem-solving in the final generalized assessment. According to relation (1), the ranking of the candidates could be done by considering three types of criteria with different importance. Thus the model becomes more flexible to defined groups of criteria that can be considered with different importance in determining the final candidates' ranking.

The formulated mathematical model (1) – (5) could be easily simplified if necessary by imposing a value equal to zero for one or two of the coefficients in relation (2). In this situation, the proposed model (1) – (5) will rely only on one or two of the groups of criteria. These scenarios can be useful in the selection of personnel for the implementation of a specific task and in the selection of personnel for the formation of a team for the implementation of a specific project.

4 Numerical Application

The applicability of the proposed mathematical model (1) – (5) was applied to the selection of staff to support a SCADA system of a small airport with the primary goal of detection and recognition of moving objects.

Ten candidates have submitted their documents for the position to support the SCADA system. For the evaluation, 5 indicators from the group of theoretical knowledge are considered 1) sensors (t-1); 2) signals processing (t-2); 3) protocols for communications (t-3); 4) database (t-4); 5) decision-making models (t-5). The second group of criteria related to soft skills considers 1) conflict management (s-1); 2) motivation (s-2); 3) planning (s-3) and from the third direction, the candidates need to solve a practical problem (p-1). The normalized evaluations toward all of the described indicators are shown in Table 1.

In addition to the normalized scores about theoretical knowledge (e_{it},), soft skills (e_{is}), and practical problem solving (e_{ip}), according to the proposed mathematical model (1) – (5), the importance weights between theoretical knowledge, soft skills and practical problem solving should be determined by the coefficients (α), (β) and (γ), together with the importance coefficients for the groups of criteria w_t, w_s and w_p.

Three different scenarios are investigated and the corresponding coefficients and weights for their importance are shown in Table 2.

Table 1. Normalized evaluation score of candidates toward the groups of criteria

#	**Theoretical knowledge**					**Soft skills**			**Practical problem solving**
	t-1	***t-2***	***t-3***	***t-4***	***t-5***	***s-1***	***s-2***	***s-3***	***p-1***
1	0.94	0.78	0.81	0.94	0.86	0.78	0.98	0.86	0.88
2	0.95	0.91	0.79	0.87	0.88	0.92	0.75	0.81	0.85
3	0.88	0.96	0.79	0.83	0.89	0.95	0.77	0.89	0.84
4	0.87	0.93	0.8	0.82	0.89	0.83	0.85	0.81	0.93
5	0.91	0.87	0.79	0.86	0.81	0.82	0.92	0.79	0.9
6	0.89	0.93	0.78	0.86	0.79	0.89	0.85	0.77	0.88
7	0.90	0.93	0.72	0.81	0.79	0.88	0.94	0.86	0.81
8	0.80	0.97	0.82	0.78	0.9	0.82	0.9	0.81	0.93
9	0.86	0.94	0.86	0.86	0.8	0.79	0.85	0.82	0.81
10	0.88	0.87	0.86	0.88	0.76	0.88	0.83	0.8	0.79

Table 2. Coefficients for the importance of groups of criteria and weights for the importance of indicators

Group of criteria	**Case-1**	**Case-2**	**Case-3**
Theoretical knowledge	***0.33***	***0.60***	***0.50***
t-1	0.20	0.20	0.20
t-2	0.20	0.20	0.20
t-3	0.20	0.20	0.20
t-4	0.20	0.20	0.20
t-5	0.20	0.20	0.20
Soft skills	***0.33***	***0.20***	***0.00***
s-1	0.33	0.33	0.33
s-2	0.33	0.33	0.33
s-3	0.34	0.34	0.34
Problem-solving	***0.34***	***0.20***	***0.50***
p-1	1.0	1.0	1.0

Case-1 expresses the scenario in which theoretical knowledge, soft skills, and practical problem-solving have equal importance ($\alpha = \beta = 0.33$, $\gamma = 0.34$) and the distribution of weighted coefficients between indicators takes equal importance too.

Case-2 expresses the scenario where the theoretical knowledge is predominant ($\alpha = 0.60$) regarding soft skills ($\beta = 0.20$) and practical problem solving ($\gamma = 0.20$) and the distribution of weighted coefficients between indicators remains the same.

Case-3 expresses the scenario, where theoretical knowledge and practical problem solving have equal importance ($\alpha = \gamma = 0.50$) and the group of indicators toward soft skills has no importance while the distribution of weighted coefficients between indicators remains the same.

5 Results and Discussion

Based on the proposed model (1) – (5) and the input data from the previous section, several optimization problems determining the overall performance of each candidate are formulated and solved. The ranked list of candidates based on preferences in Case-1 is shown in Figure 2.

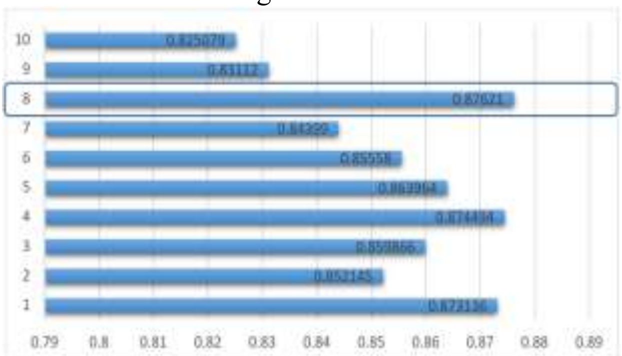

Fig. 2: Candidates ranked according to preferences from Case-1

From this ranking, it can be seen that the first place is occupied by candidate #8 with an overall performance score of 0.87621.

If the strategy for ranking needs to be changed using the preferences expressed by Case-2 are used, then the ranking of candidates acquires a different appearance, as shown in Figure 3.

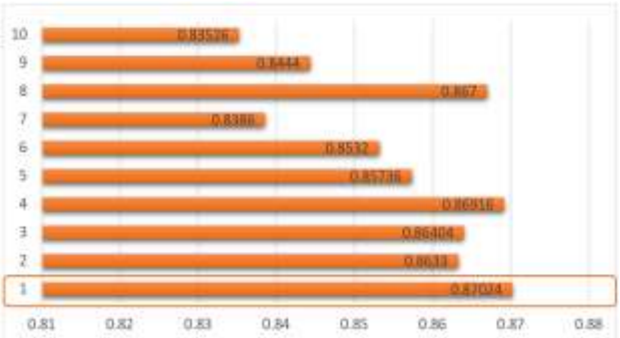

Fig. 3: Candidates ranked according to preferences from Case-2

In this situation, the first in ranking is candidate #1 with a total score of 0.87024.

According to the expressed preferences through Case-3, the corresponding ranking list of the candidates is shown in Figure 4.

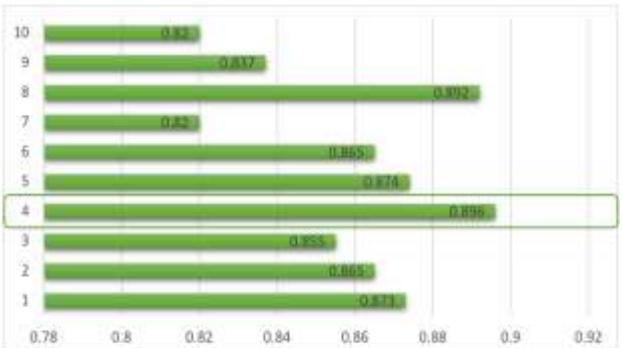

Fig. 4: Candidates ranked according to preferences from Case-3

In this ranking list, the best candidate is under # 4 with a score of 0.896.

The comparison between ranked lists of candidates according to the different preferences and using the same evaluations (Table 1) is shown in Figure 5.

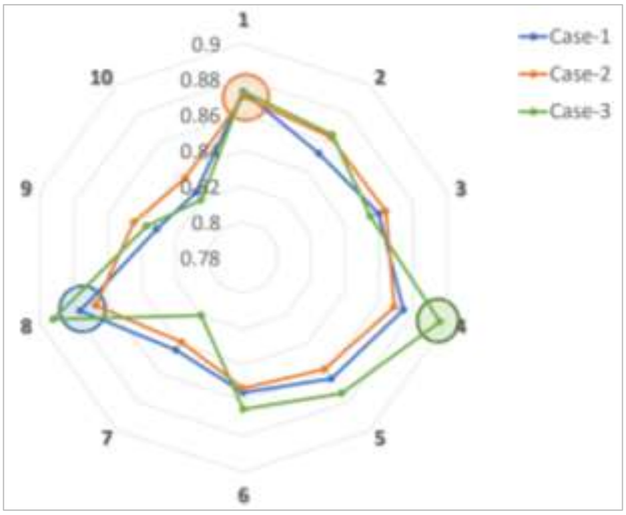

Fig. 5: Comparison between ranked candidates using different preferences

The comparison of the three simulated scenarios shows that depending on the preferences of the expert authorized for the selection of personnel, the most suitable candidate for the maintenance of SCADA systems can be determined. If all three groups of indicators are considered equally important, then the ideal candidate should be #8 as its overall performance score is the highest. If it is needed to identify a candidate with the highest theoretical knowledge less soft skills and practical problem-solving, then candidate #1 is the solution. When it is necessary to determine a candidate with theoretical knowledge and practical problem-solving, ignoring soft skills, the decision indicates that the choice is for candidate #4.

It should be noted that all of these three rankings according to the three different cases (Table 2) do not elect the same candidate. Depending on the specific situation and the required qualities of the candidate for supporting SCADA systems, it is possible to determine the appropriate candidate. For example, the ranking may give more preference to candidates with more theoretical knowledge if a candidate with development skills is sought. In situations where, for some reason, it is imperative to quickly find a candidate, then it would be inappropriate for the ranking to give preference to candidates with practical experience in solving problems.

Irrespective of the situation for choosing a suitable candidate, it is necessary to take into account some soft skills that will contribute to building a better and responsible team. All this means that the availability of various recruitment tools is a step in the right direction and can be seen as a prerequisite for increasing the quality of the staff employed.

In cases where the job description allows for working independently or working in small teams, soft skills may be overlooked in comparison to theoretical knowledge and practical problem-solving. The larger team will always require skills related to soft skills and some appropriate activities should be carefully considered to overcome such circumstances.

The use of such mathematical models contributes to achieving not only high security in the communications of complex systems such as SCADA through the selection of suitable and reliable staff for support but also to achieving better economic sustainability.

6 Conclusion

The article examines the problems of assessment and ranking with subsequent personnel selection. For this purpose, a mathematical model is proposed, which considers three separate groups of criteria regarding theoretical knowledge, soft skills, and practical problem-solving. The advantage of the proposed model is the fact that these groups of criteria can be taken into account in the final decision with different importance. The tricky element in the proposed modeling approach is the determination of the type of indicators in the criteria groups. Therefore, it is important when defining the direct duties in the job description that the qualities that the candidate must have for the specific position are formulated. This would facilitate the determination of the relevant indicators used in the proposed model for ranking the applicants. The relatively simple structure of the proposed model makes it suitable for implementation in Excel spreadsheets or it could be realized as a decision-support tool.

The proposed decision-making model for staff evaluation, ranking, and selection can be applied in various areas where some kind of assessment and subsequent choice needs to be made, for which heterogeneous data are used. The limitations of the proposed model consist in the fact that the ranking of the candidates is realized taking into account the preferences of only one authorized decision-maker. Therefore, improvements in this work and future development will be sought in formulating an appropriate model for group decision-making to consider more than one point of view in the process of assessment and choice.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed to the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare.