**Introduction (report + good practice guide)**

When dealing with changes in meteorological parameters and pollution concentrations, time and spatial scales should be considered. The spatial scale of our first simulation is of short-range only (1 km x 1 km), with a spatial resolution of 50 meters. (50 meters and research on spatial scales). The time scales we deal with can be divided into long-term and short-term scales. Our basic model uses a long-term time scale - an average yearly concentration map, upon which the optimization is performed. Our suggested module for moving the network of sensors according to long-term changes in meteorological conditions, such as **seasons**, uses as well long-term average concentrations. For such long-term changes, using a steady-state dispersion model, like the Gaussian plume model is adequate [1], [2].

For network redeployment according to short-term changes in meteorological conditions, such as **hours**, some general assumptions of the Gaussian plume model (steady-state assumptions) might not hold. We offer to both: i). address most of these assumptions by creating a suitable simulation that will enable the use of a steady-state model, and ii). solve the same problem, using a non-steady state model, and compare the results of the two approaches. The steady-state assumptions are specified below:

1. *Travel time and range of transport*. Gaussian-plume models assume pollutant material is transported instantly**,** in a straight line, to receptors that technically may be several hours or more in transport time away from the source. In the steady-state approach we will address this limitation by simulating relatively small-sized industrial areas of no more than a few kilometers wide and currently, in our initial simulation, only 1 kilometer wide. That way, when modelling the calmest conditions (low wind speed of 1 m/s), we expect pollutant that was released from one edge of the study area to reach the other edge by advection, in about 20 minutes. According to this assumption, we cannot expect to find emission deviations that occur during a shorter episode than this timescale. From a regulatory point of view, it is reasonable to assume that changes of sub-hourly timescales are only considered as noise in emission rate, while deviations that ought to be enforced must last for at least 1 hour, which is the shortest timescale we intend to use.
2. *Meteorological conditions are constant within the simulation domain and do not change during the simulated time-step*. In the steady-state approach, the spatial part of this limitation will be addressed by simulating a relatively small-sized area where spatial variations are negligible. As for the temporal limitation, in most areas, a general assumption of hourly changes in meteorological conditions holds. Exceptions are complex flow situations such as sea breeze, mountain/valley breeze, fumigation or stagnation followed by front or fumigation, that can lead to peak concentrations in the near field of a source (Broday). We will first address this issue by using meteorological data of non-complex characteristics. A short analysis of the data will first be performed to make sure the averaging time used (1-hr, 3-hr or more) is reasonable (see APPENDIX X for example) – average diurnal change in speed, direction, SC (per season?). Number of unique in an hour.
3. ﻿*Each time-step is separate and independent of previous time-steps: no memory of pollutant location or emissions from previous hours.* In the steady-state approach, we will assume no memory and hence no accumulation of pollutants between time steps exist. For complex meteorological situations, such as long-lasting calm winds and temperature inversions, this assumption might be problematic. However, these situations are usually rare in most areas. Comparison between the two approaches (steady-state and non-steady state), as we intend to perform, will help to quantify the frequency of these events in the used meteorological dataset and the discrepancy in the results such events might create.

To conclude, according to (**report**), for applications relevant to our study, such as accidental releases or regulatory impact assessments, steady-state modelling is often sufficient for short-range distances. Problems may arise ﻿if the area of interest either experiences many calm periods or if it includes a physical boundary affecting micrometeorology, such as a coastline or a valley. A decision diagram for determining whether a steady-state model or a non-steady-state model should be used according to the relevant application, is displayed in APPENDIX X.

**Literature** **review**

Many regulatory assessments are commonly simulated using simple Gaussian plume models for **annual average concentration estimations**. Lutman et al. (2004) compared between the performance of a steady-state model (the Gaussian plume model) and a non-steady-state model (a Lagrangian particle based model) in a regulatory impact assessment of routine nuclear discharges. One of the conclusions of the study was that the difference between the annual average concentrations of radiative pollutants for the two models was within the accuracy of the models themselves. Paine et al. (2012) studied the **range limit** differences between a steady state plume model and a non-steady-state puff model and found concentration ratios of almost 1 within 5 km range, and of a factor of 2 within 20 km. Levy et al. (2008) attempted to quantify the **coastal recirculation effect on air pollutants**. They used a dataset of 30-minute averages of meteorological and air pollution data at 29 monitoring stations located at three air sheds along the Israeli coastline and at inland locations. They found that the highest concentrations of primary pollutants such as NOx and SO2 were measured when the daily average wind speeds were low, and particularly under poor ventilation conditions.

**Moving sensors (methods)**

The general procedure of moving the sensors (due to expected changes in meteorological conditions) can be divided into two separate problems:

1. **Long-term time scales (e.g., seasons).** In these time scales, the optimization placement problem will first be solved separately on both configurations, using a steady-state plume model for the calculations of the average concentration fields of these time scales (upon which the PED is eventually calculated). Given two separate optimal solutions (st and st+1), assuming with the same inventory of sensors, we will then define a new multi-objective optimization problem that seeks to:
2. **minimize the total movement cost**. The cost will be a function of the number of redeployed sensors and their type (assuming different sensor types have differentoperational expenses).
3. **minimize the difference in PEDs between optimal solution st+1 and the suggested alternative during the optimization.**

The operational relocation time (i.e., the time required to redeploy all sensors), which is a function of the moving distance, will not be regarded at this stage due to the long-term time scale of the problem. The output of the optimization will be a set of redeployment alternatives, having different performances and costs. An analysis will be performed on the weather data to extract long-term “weather modes”, such as seasons (see APPENDIX X). It should be noted that in the absence of forecasts for such scales, our long-term redeployment strategy offers in fact to use a “statistical forecast”, which is based on weather averages from previous years.

1. **Short-term time scales (e.g., hours).** The time-scale by which we want to redeploy the sensors, should be the time-scale we assume no major changes in weather conditions occur. Hence, it cannot be longer than a few hours, depending on the area. As previously mentioned, the shortest time-step we intend to use is 1 hour. Too short of a redeployment time-scale would necessitate a dynamic redeployment procedure due to limitations of redeployment operational time. Two steps should first be considered for the short-term time scales:
2. Similarly to the seasonal analysis, a time-series analysis will be performed on the weather data and a characteristic time by which weather usually changes will be recognized and chosen (e.g., 1-hr, 3-hr, 6-hr, 12-hr). The characteristic weathers will be regarded as short-term “weather modes”. (APPENDIX ?)
3. A transition matrix will be calculated between characteristic weather modes in order to analyze what are the most frequent transitions between modes.

For these short-term time scales, we suggest two optimization options; in the first, we will use the steady-state assumptions as before, meaning – independency between two weather modes, between two time-steps. A redeployment strategy will then be calculated between each two concentration maps, derived according to the two independent weather modes.

In the second option, we will use a non-steady state dispersion model, such as CALPUFF, to account for memory of concentrations from the previous k time steps. A redeployment strategy will be calculated between two concentration maps, each derived according to previous k weather modes.

In the short-term time scales, the operational relocation time (i.e., the time required to redeploy all sensors), which is a function of the moving distance, will be regarded as a constraint or as an additional/alternative objective. Calculating the cost of moving the sensors might be irrelevant for the case of short-time field measurements, where sensors don’t necessarily need to be set for a long-term placement.

Once the theoretical examination of the redeployment strategies is achieved, a Markov chain (first order chain for the steady-state assumption and k-order chain for the non-steady-state assumption) will be generated, to simulate a time-series of weather modes, as well as a forecast of future weather conditions. The Markov chain will enable an evaluation of the network performance, by coupling the deployment model with a synthetic emission series. A detailed evaluation procedure will be established later in the study.

Possibly, on later stages, we will consider a new redeployment strategy, that takes into account the weather forecast of the next few weather modes, and decides whether to redeploy the network now, or later, according to a broader cost-effective perspective.

(STAGE 3 IN THE PROPOSAL).

A close up of a map

Description automatically generated

I personally think I should invest more in the CHEKING OF MY METHOD (ML!). I might need to compare it to a ring in a more far radius…. However! I should remember that a ring might work for saying that concentrations are above a certain threshold, but it won’t help me determine which of the plants did the HARIGA.

Time-scales of changes in emissions and time-scales of changes in meteorology.

Spatial-scales are important as well…

Gaussian plume model assumptions and limitations (guide):

1. ﻿Gaussian-plume models assume pollutant material is transported in a straight line instantly to receptors that technically may be several hours or more in transport time away from the source. We address this limitation (known as “the causality issue”) by simulating relatively small-sized industrial areas of no more than a few kilometers wide, and currently only 1 kilometer wide. That way, when modelling the most calm conditions (low wind speed of 1 m/s), we expect pollutant to reach the edge of the study area by less than 17 minutes. This assumption eventually says that we cannot expect to find emission deviations that occur during a shorter episode than this time-scale. From a regulatory point of view, it is reasonable to assume that changes of such short time-scales are only considered as noise in emission rate, while deviations that ought to be enforced must last for 1 hour or more. Such assumption imposes a limitation on the size of the study area to be smaller than 3.6 km wide.
2. Coastal environment or complex terrain usually create non-uniform meteorology. It is recommended not to use Gaussian plume model in these conditions.
3. Memory - ?

**Report:**

﻿The focus of the study was to look at the effects of **temporal changes in meteorological conditions on the pollutant plume** when travelling between source and receptor.

﻿

Non-steady-state models should be required to simulate dispersion applications occurring when meteorological conditions change significantly ﻿at any time or place between the source and the receptors.

during the time it takes for pollutants to travel from source to receptor

This might happen in coastal areas (and during inversion/low…).

In most areas however, the general assumption of hourly changes in meteorological conditions holds.

Assumptions of steady-state:

1. ﻿(a) Conditions do not change over time - Over the time period needed for the plume to reach each receptor, the meteorological conditions are assumed to be constant. ﻿Source characteristics, including emission rates, exit temperature and exit velocity are constant.
2. (b) ﻿Each hour is separate and independent of previous hours: No memory of pollutant location or emissions from previous hours are required.
3. (c) ﻿Meteorological conditions are constant within the modelling domain, which is true for most steady-state models, some having the capability to deal with varying terrain by modelling linear flow around complex terrain.

﻿Since in steady-state models all time steps are independent, no accumulation of pollutants can be simulated. ﻿Pollutant accumulation above the top of the planetary boundary layer before morning fumigation or pollution accumulation in a calm wind area before a sudden change in wind direction and intensity are situations that a steady-state model fails to simulate correctly. Similarly coastal fumigation associated with an onshore breeze and a change of mixing height between a coastal source and an inland receptor requires non-steady-state modelling.

﻿Therefore, steady-state models are usually acceptable to compute annual averages at receptors close enough to the source for the pollutant to reach them within a time step or within the time scale of typical weather events in the area, and provided the trajectories to the receptors are straight line (for most steady-state dispersion models)

**Accidental releases**

﻿For distances smaller than a transitional distance and timescales of a few hours, simple modelling could be adequate if the local spatial conditions are not too complex and the meteorological conditions are slowly changing.

**Regulatory impact assessment**

﻿Steady-state modelling is often sufficient for short range impact, although not always if the area of interest either experiences many calm periods or if it includes a physical boundary affecting micrometeorology, such as a coastline or a valley.

﻿For near-field (up to 10 km­) impact of a regulatory impact assessment over short timescales, the use of simple steady-state models can be questioned. Some complex flow situations such as sea breeze, mountain/valley breeze, fumigation or stagnation followed by front or fumigation can lead to peak concentrations in the near-field of a source and cannot be accurately modelled by a simple steady-state model.

The problem with certain areas of certain met behavior, the problem with memory and the problem with straight trajectories will be reviewed by a comparison of two models.

Promising:

Using a more sophisticated air pollution dispersion model (a non-steady-state model) will enable us to account for **spatial** changes in meteorological conditions, **topography** and **memory of previous hour’s emissions.** Some ﻿steady-state models have the capability to deal with varying terrain by modelling linear flow around complex terrain.

יש שתי בעיות שונות – האחת, זמן ההגעה בפועל של מזהם לעומת המודל שמניח הגעה מיידית. את הבעיה הזאת ניתן לפתור על ידי אי אכיפה של פליטה מוגברת אם נמשכת מתחת לאיקס זמן. בעיה זו קשורה גם להנחה לגבי הזמן בו משתנה מזג האוויר. בעצם לא הגיוני "לשנות" את מזג האוויר לפני שהגיע המזהם לנקודה הכי רחוקה. ואז נותרה הבעייה הכי קריטית אולי – זיכרון. מודל הסטדי סטייט אינו לוקח בחשבון אופציה של זיכרון ולכן מדמה סיטואציות של שיווי משקל, לא משנה כל כך באיזה רזולוצית זמן, כשאופציות של אגירת מזהמים למשל אינה אפשרית. בעיה גם **בקו ישר**...

לפיתרון הכללי סטדי סטייט (שימוש בממוצע שנתי) – אין בעיה.

למעבר בין עונות – גם יחסית אין בעיה.

הבעיה היא נגיד ברזולוציה של יום או שעה. אז חייבים להשתמש במודל לא סטדי סטייט.

\*Need to do some time-scale analysis of the meteorological data. Maybe compare coastal Vs. non.

**Moving sensors**

The general procedure of moving the sensors (due to expected changes in meteorological conditions) can be divided into two separate problems:

1. **Long-term time scales (e.g., seasons).** In these time scales, the optimization placement problem will first be solved separately on both configurations, using a steady-state plume model for the calculations of the average concentration fields of these time scales (upon which the PED is eventually calculated). Given two separate optimal solutions (st and st+1), assuming with the same inventory of sensors, we will then define a new multi-objective optimization problem that seeks to:
2. **minimize the total movement cost**. The cost will be a function of the number of redeployed sensors and their type (assuming different sensor types have differentoperational expenses).
3. **minimize the difference in PEDs between optimal solution st+1 and the suggested alternative during the optimization.**

The operational relocation time (i.e., the time required to redeploy all sensors), which is a function of the moving distance, will not be regarded at this stage due to the long-term time scale of the problem. It should be noted that in this problem, we basically consider a long-term time scale forecast that is based on weather averages from previous years. The output of the optimization will be a set of redeployment alternatives, having different performances and costs.

1. **Short-term time scales (e.g., hours).** The time-scale by which we want to redeploy the sensors, should be the time-scale we assume no major changes in weather conditions occur. Hence, it cannot be longer than a few hours, depending on the area. On the other hand, we wouldn’t want the time-scale to be too short, so the network would be able to separate between concrete changes in emissions and natural fluctuations (i.e., noise). In addition, too short of a redeployment time-scale would necessitate a dynamic redeployment procedure due to limitations of redeployment operational time.

Two additional steps should first be considered for the short-term time scales:

1. A time-series analysis should be performed on the weather data (similar to the seasonal analysis), and a characteristic time by which weather usually changes should be recognized and chosen (e.g., 3-hr, 6-hr, 12-hr). The characteristic weathers will be regarded as “weather modes” (shouldn’t it be done FIRST for all time scales???)
2. A transition matrix will be calculated between characteristic weather modes.

For these short-term time scales, we suggest two optimization options; in the first, we will use the steady-state assumptions as before, meaning – independency between two weather modes, between two time-steps. A redeployment strategy will then be calculated between each two concentration maps, derived according to the two independent weather modes.

In the second option, we will use a non-steady state dispersion model, such as CALPUFF, to account for memory of concentrations from the previous k time steps. A redeployment strategy will be calculated between two concentration maps, each derived according to previous k weather modes.

In the short-term time scales, the operational relocation time (i.e., the time required to redeploy all sensors), which is a function of the moving distance, will be regarded as a constraint or as an additional objective.

Once the theoretical examination of the redeployment strategy is achieved, a Markov chain (first order chain for the steady-state assumption and k-order chain for the non-steady-state assumption) will be generated, to simulate a time-series of weather modes, and a forecast of future weather conditions.

Possibly, on later stages, we will consider a new redeployment strategy, that takes into account the weather forecast of the next few weather modes, and decides whether to redeploy the network now, or later, according to a broader cost-effective perspective.

(STAGE 3 IN THE PROPOSAL).

I personally think I should invest more in the CHEKING OF MY METHOD (ML!).

Two main problems in s.s: 1) spatially constant wind field. If area is small, not a bad assumption. Complex terrain and near sea areas might be problematic for this assumption. and 2) memory.

How about taking s.s solutions for a time series and smooth them (maybe give lower and lower weight for the more far time periods (is that the plume segmented approach?).

2. The operational relocation time (i.e., the time required to redeploy all sensors) will be regarded **as a constraint**, to avoid situations where the execution of the redeployment plan lasts longer than the time period it was originally applied for.

סקאלת הזמן שבה אני רוצה להזיז חיישנים היא סקאלת הזמן בה אני מניחה שמזג האוויר אינו משתנה ולכן היא לא יכולה להיות ארוכה מידי. מצד שני, היא לא יכולה להיות קצרה מידי בגלל שאז אנחנו עוברים לבעיה דינאמית. וגם, אם קצר מידי יהיה לנו קשה להפריד בין שינויים במקור שהם רעש לבין הפרה משמעותית בפליטה.

בכל צעד זמן כזה, אני צריכה לקבוע, לפי התחזית לצעד זמן הבא, האם כדאי לי להזיז את הרשת או לא. גם אופציה של לא להזיז כלל (אפס עלות ומרחק מקסימלי בין הפתרון האלטרנטיבי לבין האופטימלי (ב-t+1) צריכה להילקח בחשבון)

צריך לחשוב על ההבדל בסקאלות כעל המון כדורים שנופלים מהשמיים. באופציה הראשונה אני אומרת – אני לא זזה ואני רק מנסה לבחור את המקום בו כדאי לעמוד כך שאתפוס כמה שיותר כדורים, בתוחלת. באופציה השניה, אני מנסה לרוץ מהר ממקום למקום ולתפוס כדור כדור.

Aside for coastal areas and complex terrains, it is a reasonable assumption that weather conditions change at the scale of 3 to 6 hours (**do some statistics**).

The optimization problem is similar to the one performed for the long-term time scales, with three main differences:

1. A time-series analysis will be performed (similar to the seasonal analysis), this time to recognize states/modes of the several hours scale (3-hr, 6-hr).
2. The non-steady state model will have memory of the steady-state solution of the last time step (?).
3. The operational relocation time (i.e., the time required to redeploy all sensors), which is a function of the moving distance will be regarded as well, as a constraint or as an additional objective.

Two main problems in s.s: 1) spatially constant wind field. If area is small, not a bad assumption. Complex terrain and near sea areas might be problematic for this assumption. and 2) memory.

How about taking s.s solutions for a time series and smooth them (maybe give lower and lower weight for the more far time periods (is that the plume segmented approach?).

2. The operational relocation time (i.e., the time required to redeploy all sensors) will be regarded **as a constraint**, to avoid situations where the execution of the redeployment plan lasts longer than the time period it was originally applied for.

**Now – we consider possible changes between pairs of situations. This will require knowledge on a diurnal cycle for example – Markov chain – if I define in advance some “states” – I can derive the transformation matrix. And then perform analysis on these changes only. Another tool – ARIMA time series prediction in python.**

At later stages, we will combine the technique developed in (2) with longer forecasts and the optimization procedure will try to account for a more general solution.

﻿

עוד משהו שצריך לבחון – ריכוך הפתרון - אולי עבור כל מצב מזג אוויר אפשרי (מה-144) לפתור בנפרד את הפתרון האופטימלי. ואז להציג על מפה אחת את כל הפתרונות (עם משקל לפי תדירות המצב המטאורולוגי) ולסמן אזורים חשובים. כרגע אני מניחה מפה ממוצעת שנתית של תנאי מזג אוויר, עבור כל מקור. אולי עם קלאסטרינג. לקלסטרינג אין ממש משמעות כרגע. אולי אם נעבוד עם שדה רוח במקום רוח קבועה במרחב, אפשר לנסות לעשות clustering של שדות הרוח האלו כדי לחלק למצבים שונים.

בנוסף, אפשרי לבחון סיטואציה שבה יש גם חיישנים סטטיים, כמו תחנות AQM.

בנוסף להשוואה של מפת הריכוזים הממוצעת, להשוות למפה **עם שונות הריכוזים** הגבוהה ביותר.

אני חושבת שאולי אין הבדל בין ה-ס.ס ללא ס.ס אם המקורות שלי כל הזמן פולטים בצורה ס.ס.

ה-רעיון שלי לשיטה אחרת – יצירה סטוכאסטית של מלא מצבי פליטות יתר (אפשר גם בהתבסס על נתוני אילן לוי) וסיווג לפלט מעל לעומת מתחת למותר. ואז לעשות אופטימיזציה כדי למצוא את סט החיישנים שמקטין את השגיאה של המודל (random forest נגיד). האם יקח לי מלא זמן להריץ? כנראה שכן....

ה-CULPUFF ייתן לי hourly concentrations.

כדי לבחון את המודל שלי אני פשוט צריכה להריץ את סדרת הזמן ה-15 שנתית שלי (שעתי) של מזג האוויר ולהמציא וריאציות (שעתיות) של פליטות של המקורות שלי על סדרת הזמן של מזג האוויר ולראות האם אני יכולה לבנות מודל שמאתר את החריגות האלו. / לבצע source-term estimation.

סיכום:

1. **אופציה א'** – מה שעשיתי עד עכשיו, מפה משוקללת (segmented approach?) ואופטימיזציה עליה. **~~אופציה ב'~~** ~~- להריץ אופטימיזציה עבור 100+ מצבי מזג האוויר כדי לקבל פתרונות אופטימליים עבור מפת הריכוזים שכל מצב מייצר. מתוך זה לייצר מפת עדיפויות עם משקל גבוה יותר למצבים השכיחים.~~
2. הזזת החיישנים כתלות ב-Time scales -

זמנים ארוכים – לעשות אופציה א' ~~או ב'~~ על עונות.

זמנים קצרים – (1) steady-state – זיהוי מצבים אופייניים 6 שעתיים או 3 שעתיים. לפתור s.s לכל מצב (להניח רשת של x חיישנים כדי לחסוך זמן הרצה? במילא בשלב הזה כבר "הרשת פרושה") (2) לפי אופציה ב'

סקאלת הזמן שבה אני רוצה להזיז חיישנים היא סקאלת הזמן בה אני מניחה שמזג האוויר אינו משתנה (נגיד, כל 6 שעות). בכל צעד זמן כזה, אני צריכה לקבוע, לפי התחזית לצעד זמן הבא, האם כדאי לי להזיז את הרשת או לא. גם אופציה של לא להזיז כלל (אפס עלות ומרחק מקסימלי בין הפתרון של t לבין t+1 צריכה להילקח בחשבון)

1. בחינה של הרשתות.
2. לעשות – אנליזה של סקאלות-זמני רוחות, מערך הטרוגני, להפוך את המידע של מזג האוויר לשעתי.

~~it might be problematic to assume no memory of concentration locations~~ **~~or emissions~~** ~~from the previous hours, as assumed by a steady-state model. Hence, a non-steady state dispersion model will be used, such as CALPUFF.~~ The highest resolution that will be considered is of a few hours, in order to deal only with redeployment of a static network. Higher resolution than of a few hours turns the problem into a dynamic redeployment problem of mobile sensors.

לבדוק איזה ממוצע שעות לקחת –

1. אופציה אחת היא להגיד – לרוב מודלים של מזג אוויר הם ברזולוציה של 3 או 6 שעות, בזמנים מייצגים ביום. ללכת לפי זה
2. בעזרת rolling, לעשות std על חלונות בגדלים שונים ולקחת את הממוצע. ממוצע ה-std גדל ככל שמגדילים את החלון. מאפשר לראות מה סדר הגודל של מהירות וכיוון הרוח אבל
3. בעזרת resample, לעשות std על זמנים שונים
4. לעשות diff בין 2 צעדי זמן ולהבין מה מספר צעדי הזמן האופייניים לשינוי משמעותי או את הזמנים ביום שזה משתנה (למשל תנאי יציבות). אולי היסטוגרמה.
5. בערך כמו 4 – אוטוקורליישן.

בשביל לדעת מה ה-k צעדי זמן שצריך לקחת בחשבון, אפשר לבצע partial autocorrelation.

﻿the US EPA website

(http://www.epa.gov/scram001/dispersion\_prefrec.htm) and John Irvin’s website (http://jsirwin.com/Tracer\_Data.html) can be consulted

s **Robe et al., 2002 –**

Developed an online forecast-warning system that ﻿predicts periods when meteorological conditions are more likely to lead to high pollutant concentrations.

**הטרוגניות**

|  |  |  |
| --- | --- | --- |
| **Detection threshold** | **Dynamic range** | **Price ($)** |
| high | high | 1000 |
| low | high | 500 |
| high | low | 250 |
| low | low | 50 |

1. מגדירים מראש 4 סוגים של חיישנים לפי הטבלה הנ"ל.
2. מערך חדש של decision variables מתחלק ל-5 חלקים :

קטן מ-0.2 – אפס, לא מניחים חיישן.

0.2-0.4 – מניחים חיישן א

0.4-0.6 – מניחים חיישן ב

0.6-0.8 – מניחים חיישן ג

0.8-1 – מניחים חיישן ד

1. לפי המערך הזה מתרגמים למחיר הרשת ומספר החיישנים.

2. לפי המערך הזה מתרגמים ל-dyr ו-thr ואיתם מחשבים את ה-PED.

3. ממקסמים PED וממנממים מחיר רשת.

**איוואלואציה**